Physiological Pattern Analysis: A Key to Improved Biofeedback Systems for the Voluntary Control of Events in Consciousness

By

Tim Scully

DISSERTATION

Presented to

the Humanistic Psychology Institute

in Partial Fulfillment

of the requirements for the degree

Doctor of Philosophy

In

Psychology

This dissertation was prepared for presentation to, and accepted by, the following committee

Sam Keen, Ph.D.

Stanley Krippner, Ph.D.

Arne Collen, Ph.D.

Date degree conferred - June 29, 1979

Physiological Pattern Analysis: A Key to Improved Biofeedback Systems for the Voluntary Control of Events in Consciousness

By

Tim Scully

Physiological Pattern Analysis: A Key to Improved Biofeedback Systems for the Voluntary Control of Events in Consciousness

By

Tim Scully

ABSTRACT

This study investigated the effectiveness of a new approach to the analysis of patterns of physiological response, for the purpose of finding correlations with events in consciousness. The design of a microcomputer system for the collection and real-time analysis of physiological data is described, with circuitry and software for the analysis of two EEG channels by amplitude-period and phase analysis.

A study is reported in which physiological correlates of five identity states (Berne, 1961; Tart, 1975) were sought in peripheral skin temperature, galvanic skin response (GSR), basal skin resistance (BSR), muscle tension (EMG) and temporal EEG from the right and left hemispheres. The identity states were evoked by cartoons from the Ego State Inventory (McCarley,1974) and identified by subjective reports in the form of multiple-choice responses to the cartoon test items. Useful data were collected from four subjects. Each subject viewed 49 slides and chose one of five responses for each.

The EEG data were analyzed in 16 dimensional subsets, corresponding to 16 frequency bands and 16 phase angle bands. EEG data from each hemisphere were analyzed as amplitude density, average amplitude and frequency of occurrence spectra.

Differences among the five identity states were significant at the .05 level, according to multivariate analysis of variance of the non-EEG and left hemisphere EEG data. The results of univariate and multivariate analyses of variance are reported for the various physiological measures.

The Adult ego state showed the lowest arousal in all measures and the Parent ego state showed the highest arousal in all measures. Amplitude-period analysis of EEG was shown to be a useful analytical method for finding EEG correlates of identity states, and discriminant analysis proved to be a fruitful approach to physiological pattern analysis.

PREFACE

The viewpoint of the experimenter can influence the outcome of research and inevitably colors its presentation. Humanistic psychology concerns itself with subjective experience more than most scientific disciplines, and thus it is reasonable for me to briefly introduce myself and tell a little of the story of how this research came about.

I was born in 1944, and was raised in a family where scientific knowledge was highly valued, but considered primarily limited to the measurable and tangible. My parents were Irish Catholic and English Protestant, and both were bitter about the religious conflict which their marriage triggered. My one brother and I were raised without formal religious training.

I was an amateur scientist from an early age, and always had a small workshop or laboratory for experiments in physics or chemistry. I began working at the University of California Lawrence Radiation Laboratory at age 15 and entered the University as an undergraduate student in physics and mathematics. I had little social experience and was usually alone. I lived in my grandparent's attic, worked at the Radiation Laboratory and began doing consulting electronics design work while an undergraduate.

In 1965 a friend who was studying Oriental Philosophy interested me in mysticism and marijuana. Shortly thereafter, I took LSD, seeking a mystical experience. I was not disappointed, and my life changed drastically. With all the fervor of a fresh convert, I wanted to share my ecstatic experiences from LSD with everyone, and I set out to manufacture and give away large quantities of psychedelic drugs.

I lived in the psychedelic "underground" until 1969, as a drug manufacturer, believing that I was performing an important public service. In 1969, after an arrest on drug charges (which were eventually dropped), I began to realize that the ideals of the "flower children" and the realities of the drug sub-culture had drifted very far apart. I ended my involvement with drugs.

In 1968 I was a subject in one of Barbara Brown's early experiments with brainwave biofeedback, and became fascinated by the possibility of learning voluntary control of states of consciousness through biofeedback training. In 1969 I started a small biofeedback instrument manufacturing corporation, Aquarius Electronics, with the idea of developing biofeedback instruments which might be useful in education.

My former associates in the drug "underground" did not end their involvement when I did and went on to become the targets of a major government investigation. I was eventually indicted for conspiring with them in 1968 and 1969 and in 1974 I was tried on these felony charges. I -was convicted and sent to McNeil Island Penitentiary with a 20 year prison term, because of the scope of my manufacturing activities, and because of my involvement with drug sellers. When I was sentenced, the judge expressed concern for the victims of drug abuse.

I was released on appeal bond and in 1975 became a Research Fellow of the Humanistic Psychology Institute. I contracted to study the development of biofeedback systems and methods for applying them in drug rehabilitation. I began volunteer work in community drug programs in San Rafael and Mendocino, California. I did not find many victims of psychedelic drug abuse, but I did become interested and involved in the problems of alcohol and polydrug addicts. In nearly three years of work in three different programs, using conventional biofeedback systems, I became increasingly aware of the limitations of simple biofeedback training. In work at Gladman Memorial Hospital in Oakland, California, I was able to test an innovative approach to biofeedback training, but was still not satisfied.

This dissatisfaction led me to focus my research on the development of more sophisticated biofeedback systems which could be used in training for control of states of consciousness more specific than stress and relaxation. I lost the appeals of my convictions in 1977 and was ordered to report back to McNeil Island Penitentiary to resume serving my sentence. This interrupted the experimental work described in this dissertation and greatly slowed the data analysis portion of the research.

Thanks to the assistance and cooperation of the Education and Psychology Service departments of the prison I was allowed to remain intellectually active. Under the supervision of Dr: D. B. Nakashima, I established a biofeedback stress management training program at the prison. In cooperation with a U.S. Probation Officer, who had supervised me on appeal bond, and the Education Department, I was eventually allowed to develop and program a microcomputer communication system for a nonvocal handicapped young lady. This computer work also made it possible for me to complete the data analysis for this dissertation.

This dissertation was written inside McNeil Island Penitentiary. Work on it has helped to make my experience of prison a meaningful and educational one. I hope to continue the research which is begun here, after my return to society.

I owe thanks to many people for help in making this work possible. Among them are the staffs of HPI, McNeil Island Penitentiary and Aquarius Electronics, my mother, my brother and Amelia Garcia.

TABLE OF CONTENTS

LIST OF TABLES

Chapter 1

INTRODUCTION

The extreme determinist or behaviorist view of people is that they are robots or computers, programmed by genetic predisposition and environmental inputs (Green & Green, 1977, p. 61). The humanistic view of people holds that, although they may be biocomputers programmed by genetic and environmental inputs, they also have volition, free will. We can metaprogram the human biocomputer (Lilly, 1972); we can choose how to view our environment and change our responses to stimulation.

It is widely accepted that our experience of the world is modified greatly by cognitive processes, that we create our own reality through selective perception. James (1902/1958) wrote that "our normal waking consciousness...is but one special type of consciousness, whilst all about it, parted from it by the filmiest of screens, there lie potential forms of consciousness entirely different....No account of the universe in its totality can be final which leaves these other forms of consciousness quite disregarded."

Huxley (1954) spoke of a mental "reducing valve" which is part of our perceptual mechanism. This reducing valve filters the torrent of incoming sensory data down to a manageable volume, but at the same time, it forces us to construct a limited model of reality.

Our consciousness varies from moment to moment. A quotation from Ouspensky's (1949) report of George Gurdjieff's early lectures on philosophy expresses this idea very clearly:

> "One of man's important mistakes," he said, "one which must be remembered, is his illusion with regard to his I.

"Man such as we know him, the 'man-machine,' the man who cannot 'do,' and with whom and through whom everything 'happens,' cannot have a permanent and single I. His I changes as quickly as his thoughts, feelings and moods, and he makes a profound mistake in considering himself always one and the same person; in reality he is always a different person, not the one he was a moment ago.

"Man has no permanent and unchangeable I. Every thought, every mood, every desire, every sensation, says 'I.' And in each case it seems to be taken for granted that this I belongs to the Whole, to the whole man, and that a thought, a desire, or an aversion is expressed by this Whole. In actual fact there is no foundation whatever for this assumption. Man's every thought and desire appears and lives quite separately and independently of the Whole. And the Whole never expresses itself, for the simple reason that it exists, as such, only physically as a thing, and in the abstract as a concept. Man has no individual I. But there are, instead, hundreds and thousands of separate small I's, very often entirely unknown to one another, never coming into contact, or, on the contrary, hostile to each other, mutually exclusive and incompatible. Each minute, each moment, man is saying or thinking 'I.' And each time his I is different. Just now it was a thought, now it is a desire, now a sensation, now another thought, and so on, endlessly. Man is a plurality. Man's name is legion.

"The alternation of I's, their continual obvious struggle for supremacy, is controlled by accidental external influences. Warmth, sunshine, fine weather, immediately call up a whole group of I's. Cold, fog, rain, call up another group of I's, other associations, other feelings, other actions. There is nothing in man able to control this change of I's, chiefly because man does not notice, or know of it; he lives always in the last I. Some I's, of course, are stronger than others. But it is not their own conscious strength; they have been created by the strength of accidents or mechanical external stimuli. Education, imitation, reading, the hypnotism of religion, caste, and traditions, or the glamour of new slogans, create very strong I's in man's personality, which dominate whole series of other, weaker, I's. But their strength is made up of the 'rolls' [as in player piano rolls or computer programs] in the centers. And all these I's making up a man's personality have the same origin as these 'rolls'; they are the results of external influences; and both are set in motion and controlled by fresh external influences.

"Man has no individuality. He has no single, big I. Man is divided into a multiplicity of small I's.

"And each separate small I is able to call itself by the name of the Whole, to act in the name of the Whole, to agree or disagree, to give promises, to make decisions, with which another I or the Whole will have to deal. This explains why people so often make decisions and so seldom carry them out. A man decides to get up early beginning from the following day. One I, or a group of I's, decides this. But getting up is the business of another I who entirely disagrees with the decision and may even know absolutely nothing about it. Of course the man will again go on sleeping in the morning and in the evening he will again decide to get up early. In some cases this may assume very unpleasant consequences for a man. A small accidental I may promise something, not to itself, but to someone else at a certain moment simply out of vanity or for amusement. Then it disappears, but the man, that is the whole combination of other I's who are quite innocent of this, may have to pay for it all his life. It is the tragedy of the human being that any small I has the right to sign

> checks and promissory notes and that the man, that is, the Whole, has to meet them People's whole lives often consist in paying off the promissory notes of small accidental I's." (pp. 59-60)

Tart (1975) has proposed a systems model of consciousness in which Gurdjieff's I's are called identity states. People normally shift from identity state to identity state rapidly without being aware of the change, identifying completely with each state. There are also larger changes in consciousness with which most people are familiar. Tart calls these discrete states of consciousness (d-SoC's) because they are so different from each other and are lacking in smooth continuity between each other. Examples of d-SoC's include: the normal waking state, nondreaming sleep, dreaming sleep, hypnosis, alcohol intoxication, marijuana intoxication and meditative states (Tart, 1975, p. 5).

A d-SoC is a unique, dynamic pattern or configuration of psychological structures, an active system of psychological subsystems, stabilized by a number of processes so that it retains its identity and function (Tart, 1975). The subsystems Tart lists are: extroperception, introperception, input processing memory, sense of identity, subconscious, emotions, space/time sense, motor output and evaluation (Tart, 1975, p. 6).

Metaprogramming the human biocomputer, to use Lilly's (1972) metaphor, implies learning to be aware of shifts in identity state, changes in consciousness, and to be in control of them. This has been a traditional goal of spiritual disciplines such as meditation and yoga. If it is possible, it clearly is not a simple task, since few if any people can demonstrate this skill.

Some scientists, particularly behaviorists, argue that consciousness is too ephemeral a subject for true scientific study because it is not accessible to objective measurement and rigorous study. Such researchers usually avoid the use of mentalistic terms such as thinking. They consider thought to be simply covert speech (Skinner, 1971, 1976), while emotions are considered to be labels which people attach to complex physiological processes, e.g., fear may be an odd feeling in the abdominal region.

There is an increasingly convincing body of evidence, which will be discussed in detail later, indicating that there may be measurable physiological correlates of events in consciousness, patterns of physiological response associated with emotions, identity states and states of consciousness. There is also a growing body of evidence that any physiological process which can be measured may be brought under some degree of voluntary control through biofeedback training (Green & Green, 1977). This suggests the possibility of learning awareness and voluntary control of identity states and states of consciousness through biofeedback training.

Statement of the Problem

The study reported here is one step along a path toward the development of powerful biofeedback systems for teaching awareness of and voluntary control of identity states and states of consciousness. A methodology for the study of identity states is suggested and tested experimentally by application to a specialized group of identity states defined by Berne (1961) as ego states and redefined by Dusay (1977a) as functional egostates (I am using ego state to indicate Berne's structural ego states and egostate to denote Dusay's functional egostates). This methodology involves the use of a computerized physiological monitoring system to collect data on patterns of physiological response from subjects who report their identity state by selecting responses to a projective test. It also involves the use of multivariate statistical methods of pattern detection and recognition, such as discriminant analysis.

Thus it is hypothesized that distinct physiological correlates of identity states exist and can be detected by computerized physiological monitoring. More specifically, it is hypothesized that distinct correlates of Dusay's (1977a, 1977b) functional egostates, as defined by subjects' responses to McCarley's (1974) test, can be identified in temporal brainwaves and other physiological measures and that techniques can be developed for the real-time identification of egostates from these correlates.

A Brief Introduction to Biofeedback

Until recently, it was commonly believed that many body processes are out of the range of conscious control. Autonomic functions such as blood pressure, peripheral skin temperature, skin resistance and peristalsis were believed to be inaccessible to will or volition. Some central nervous system processes, such as the electrical activity of the brain, were also believed to be outside the range of volition. Although Johannes Schultz, J H. Blair and a few other scientists believed, as early as the turn of the century, that such processes could be consciously controlled (Green & Green, 1977), general acceptance of this view has come only after Miller's (1969) report of operant conditioning of autonomic responses, the development and widespread application of biofeedback training techniques.

Biofeedback is simply the measurement of a biological process and the feeding back of the results of this measurement to the organism being measured. Looking in a mirror is a biofeedback process in which information about one's facial expression is fed back. Biofeedback training takes place when biofeedback information is used to learn conscious control over the process which is measured and fed back, e.g., when an actor uses a mirror to learn to produce a desired facial expression.

A wide range of body processes have been brought under conscious control through biofeedback training. Four have come into common clinical use and deserve discussion in more detail here: control over peripheral skin temperature, muscle tension, the electrical properties of the skin and the electrical activity of the brain. Although biofeedback training is sometimes done to correct physiological malfunctions, e.g., training for improved control over damaged muscles, it is the existence of relationships between physiological and psychological events which make biofeedback training an interesting metaprogramming technique.

At the present level of development of clinical biofeedback technology, training in the voluntary control of states of consciousness is practically limited to relaxation or stress management training. The stumbling block to training in more specific emotional and cognitive states is the fuzziness of the relationships between the physiological events which can be measured and trained, and the psychological events of interest. Even the relationship between psychological stress and physiological events varies from person to person and from day to day.

Despite these limitations, biofeedback training already enjoys wide acceptance both as a therapeutic modality for psychosomatic, stress related diseases and as a valuable tool for personal growth and insight.

A brief discussion of each of the four major modalities of biofeedback training follows, which is intended as preliminary to the following discussion of physiological pattern analysis and pattern biofeedback. The emphasis here is on biofeedback as it relates to events in human consciousness, and the other applications of biofeedback are not discussed. Some of the arguments against single-modality biofeedback and in support of pattern biofeedback will be presented.

Peripheral skin temperature

Cold hands and feet are a common stress response, resulting from peripheral vasoconstriction (Mittleman & Wolff, 1939). The "fight or flight response" causes the sympathetic nervous system to contract the smooth muscles in the peripheral blood vessels, reducing blood circulation and thus reducing skin temperature at the extremities. A deeply relaxed person may have a fingertip temperature of about 98 F (Fuller, 1977), while a person under stress may have a fingertip temperature several degrees colder than room temperature (Mittleman & Wolff, 1939), perhaps as low as 60 F. This relationship between stress and fingertip temperature makes biofeedback training in handwarming a popular clinical modality for stress management training (Brown, 1977; Budzynski, 1977).

Peripheral skin temperature is influenced by a number of variables, of which stress is only one. The environmental temperature has an obvious influence. A variety of drugs, including tobacco, influence peripheral vasoconstriction. Vigorous exercise increases peripheral circulation, and extended immobility decreases it. Even apart from these factors, warm hands do not necessarily imply a state of relaxation. At best, warm hands are an indication of sympathetic nervous system relaxation (Brown, 1977; Fuller, 1977).

Skin temperature biofeedback training is often done with a single temperature sensor (e.g., thermistor probe) taped to a fingertip. Inconsistent data can be collected due to variations in probe attachment technique. Time is required for heat to transfer from skin to probe, and when this delay is added to the body's natural response delay, the latency of skin temperature responses to stimulation may range from several seconds to nearly a minute. If biofeedback training is done with a single probe, occasionally a very local response is trained, in which a single finger is warmed while others remain cold (Fuller, 1977).

Skin temperature training has enjoyed success as a clinical biofeedback training modality. It has been effective in the relief of vascular (migrane) headaches and Raynaud's disease, as well as in teaching simple stress management (Fuller, 1977).

The electrical properties of the skin

The electrical properties of the skin have been studied since shortly after Galvani's discovery of the electrical properties of muscles and nerves (Neumann & Blanton, 1970). There are several different methods of measuring these properties, some of which are passive techniques which sense naturally occurring electrical potentials on the skin (EDP or electrodermal potential), while other methods use a sensing current to measure the electrical resistance (BSR or basal skin resistance) or conductance (BSC or basal skin conductance) of the skin.

The baseline levels of these measurements are influenced by many factors including temperature, drug effects, location on the skin and the subject's level of arousal. Short term fluctuations in these measures, as a response to stimulation, are sometimes called galvanic skin responses or GSR. The discovery that sensory and ideational stimuli produce GSR responses led Jung (1918) and others to use GSR responses to study events in consciousness. Although the early promise of GSR as a window into the unconscious mind has not been fulfilled, GSR and BSR measurements are considered one of the most useful physiological measures of arousal (Neumann & Blanton, 1970).

Biofeedback training in increasing skin resistance (BSR) is used as a deep relaxation technique (Fuller, 1977; Payne &

Reitano, 1977). Biofeedback training with GSR is used in systematic desensitization, a procedure in which excessive response to specific stimuli can be unlearned (Fuller, 1977). Skin resistance usually increases and the size of GSR responses usually decreases with relaxation. But some people with chronic stress have unusually high BSR and may have unusually large or unusually small GSR responses (Toomim & Toomim, 1976). The lack of a GSR response to an ideational stimulus can indicate that it is not arousing, or that the subject is under severe stress, or that the blood sugar level is low, or that skin temperature is low, etc. and thus GSR responses are often misinterpreted When carefully interpreted, GSR and BSR feedback have proven to be of real value in psychotherapy (Fuller, 1977).

Muscle tension

The relationship between electricity and muscles was discovered by Galvani in the l8th century (Basmajian, 1974), and stimulated much of the early research in neurophysiology and electricity. By the early 20th century, the electrical signals associated with muscle action began being studied (Adrian & Bronk, 1928) and the use of electromyography (EMG), to measure these signals for diagnostic and clinical purposes soon became widespread. These uses focussed on traumatic damage to nerves and muscles, or other neurological pathology, and did not involve much exploring of the relationship between muscle tension and events in consciousness until after World War II, although some psychologists did show an early interest in how patterns of muscle tension relate to psychopathology (e.g., Reich, 1949).

Although skeletal muscles are generally considered to be under conscious control, excess muscle tension is a common companion of stress, and in many subjects with chronic stress, this excess muscle tension may remain unnoticed until it becomes painful, and it may be uncontrollable (Fuller, 1977). EMG biofeedback training for the deep relaxation of tense muscles has come into common clinical use. In EMG relaxation training, a person learns to sense the difference between tension and relaxation, a process of becoming dishabituated to stress, and thus the person learns to gain control over tension and relaxation. EMG biofeedback training is also done for the retraining of damaged muscles.

EMG biofeedback training in muscle relaxation does not necessarily produce a subjective feeling of relaxation. Much EMG relaxation training has been done with the sensing electrodes placed on the frontalis muscle, on the forehead. This electrode placement was chosen because the frontalis muscle is very difficult to relax completely, and researchers attempting to cure tension headaches hoped that frontalis relaxation would generalize to other muscles (Brown, 1977). Some researchers report that such training results in subjective reports of relaxation, but it is more common for researchers to report little or no correlation between frontalis EMG and subjective reports of relaxation (Brown, l977). Some of this lack of correlation is probably due to lack of generalization of muscle relaxation from frontalis to other muscles.

EMG training has proven to be of clinical value in the relief of tension headaches, in stress management training and in the rehabilitation of damaged muscles (Fuller, 1977). It is perhaps the most widely used modality.

The electrical activity of the brain

Hans Berger (1929) is generally credited with having first recorded the human electroencephalogram (EEG), the electrical activity of the brain, by attaching electrodes to the exposed cerebral cortex. Later he measured similar but weaker signals on the scalp. Berger hoped to find an explanation for psychic phenomena in EEG measurements, but was able to find only a vague relationship between events in consciousness and EEG signals. Although researchers tried to relate EEG tracings to thoughts and feelings, for many years the only practical applications of EEG measurements were in the diagnosis of pathology such as epilepsy and brain tumors.

EEG signals are weak, complex, constantly changing and usually are different when measured at different scalp locations. For some purposes, they are classified in four broad categories on the basis of their frequency. Signals between 8 and 13 Hz (Hertz or cycles per second) are called alpha waves because these were the first pattern identified by Berger (1929). EEG signals above 13 Hz, usually weaker in amplitude than alpha, are called beta waves and were the second major pattern named by Berger. Signals between 4 and 8 Hz are called theta waves and those below 4 Hz are called delta.

Alpha waves, which are usually most prominent in the occipital lobes at the back of the head, are often associated with states of relaxation and with a lack of visual attention (the occipital lobes of the brain process visual information), while beta waves are often associated with arousal, activation and visual attention (Brown, 1977). Research on the different stages of sleep revealed that brainwaves progressively slow in frequency as sleep approaches and deepens, from beta to alpha, alpha-theta (drowsiness), a mixture of 14 Hz sleep spindles with a low voltage background (the one departure from a smooth decreasing frequency progression), increasing theta, theta-delta and finally delta during deep dreamless sleep (Dement & Kleitman, 1957). One of the earliest applications of EEG in the study of consciousness was in the study of sleep and dreaming.

Studies of the brainwaves of Zen monks (Kasamatsu & Hirai, 1966) and yogis (Anand, Chhina & Singh, 1961) revealed that these meditators have an unusual and characteristic EEG pattern consisting of unusually high amplitude alpha spreading over the entire scalp during meditation. Although later research has revealed that only some forms of meditation produce this characteristic EEG pattern (Brown, 1977), these findings stimulated interest in the relationship between EEG and altered states of consciousness

Early EEG biofeedback training was used for the enhancement and suppression of occipital alpha waves (Kamiya, l969), and reports of the high alpha state were similar to those of meditators. This stimulated interest in alpha training as an aid to relaxation and meditation. Although some clinical biofeedback is now done for other purposes, e.g., SMR (sensory motor rhythm) training for control of epileptic seizures (Sterman & Friar, 1972) and theta training for imagination (Green & Green, 1977), most clinical EEG training is presently alpha enhancement and alpha suppression training (Fuller, 1977).

As with the other modalities previously discussed, the results of EEG alpha training are inconsistent. Glaros, Freedman and Foureman (1977) and Glaros (1977) found that the subject's expectations, as modified by instructions from the experimenter, were the controlling factor, and that the use of true or false feedback had little influence on subjective reports. Plotkin (1975) reported that the "alpha experience" was not necessarily associated with either pleasant emotional states or non-directed thought, as other investigators (Kamiya, 1969) had reported. Tyson and Audette (1977), on the other hand, found a significant correlation between alpha amplitude and subjective reports.

As with EMG training, part of this inconsistency may be accounted for by local training effects. A subject may learn to modify EEG activity in the single scalp area which is monitored without learning to generalize this modification to other scalp areas. Peper (1972) demonstrated that such local training can take place, and successfully trained subjects to control alpha production independently in their left and right central-temporal areas.

Another major factor in these differences, and a common problem in clinical EEG training, is the amount of time required to produce significant training effects. Hardt (1975) and Ancoli and Kamiya (1977) have pointed out that many investigators who attempt to test the effects of alpha training fail to schedule enough training to produce effects. The first few hours of training usually show an improvement in alpha density and amplitude due to relaxation and becoming accustomed to the biofeedback training situation. A decrease in alpha production often follows, while the subject experiments with different strategies for alpha enhancement. By the third to fifth hour, a real training effect becomes noticeable which continues through perhaps the twentieth hour.

Although brainwave training holds the most promise as a modality for learning voluntary control of events in consciousness, it is the least clinically applied modality. This is because it is the most complex, the most misunderstood and the most time consuming (Fuller, 1977).

A Summary of Practical Problems in Biofeedback Learning for Control of Events in Consciousness

All four modalities commonly used in clinical biofeedback can produce local training effects, in which a physiological response is learned in only a small part of the body, while the unmonitored portions of the body may remain unchanged or may change in an undesired direction. Thus, even if there are specific physiological states corresponding to specific emotional and cognitive states, conventional biofeedback training is not very successful in detecting and training for these states. There are many factors, apart from events in consciousness, which can influence physiological events. Environmental, dietary and drug effects are among the confounding factors.

A further problem, which is common to all modalities of training, though less relevant to this research, is the strong influence of expectations and suggestions on the subjective results of biofeedback training (Wickramasekera, 1976). The placebo effect will probably always be of great importance in biofeedback training (Stroebel & Glueck, 1973), though refinement of biofeedback systems which narrow the range of states of consciousness correlating with the trained physiological state may minimize the relative importance of it.

Despite the problems which limit the effectiveness of conventional biofeedback training, its successes have led to new insights into the mind/body problem and into the nature of volition. Mind and body are now more easily seen as dynamically interacting parts of a system, and volition is a metaforce which can modify the system's perception and behavior (Green & Green, 1977).

Phares (1976) has pointed out that a person's beliefs regarding locus of control are a self-fulfilling prophecy. A person who believes that he or she responds helplessly to environmental stimuli is more likely to do so than a person who feels in control of his or her responses. The demonstration of successful volitional control of internal processes through biofeedback training is slowly changing our cultural belief systems regarding locus of control and volition. As new beliefs regarding volition spread, and more people have personal experience in biofeedback training, more people will have a clearer idea of how much responsibility they can take for how they feel.

Physiological Data Analysis, Pattern Biofeedback and Events in Consciousness

Before attempting to design biofeedback systems for the voluntary control of identity states, there are several issues that need to be resolved. First, it must be established that patterns of physiological response exist which correlate well with identity states. Note, however, that it is not necessary that consciousness be purely physiological and completely measurable. Second, it must be demonstrated that biofeedback training can teach control over patterns of physiological response. And third, such training in physiological patterns must be investigated to learn if it does imply learning control over consciousness.

Physiological events and events in consciousness

Several approaches have been used in looking for patterns of physiological response correlated with states of consciousness. One approach has been simple physiological data recording of subjects who can produce a desired state of consciousness upon request. The studies of Zen monks (Kasamatsu & Hirai, 1966) and yogis (Anand, Chhina & Singh, 1961) fall into this category. These researchers were able to recognize a pattern of response (unusual abundance of high amplitude alpha waves all over the scalp) in raw recorded physiological data. The same general approach was used in early studies of sleep (Dement & Kleitman, 1957), where distinctive brainwave patterns and eye movements were found to be associated with dreaming, by observation of raw recorded physiological data.

Sadly, physiological response patterns associated with events in consciousness are rarely so easy to identify. There are many factors, some of which have already been discussed, which influence physiological responses; cognitive and affective processes are rarely the strongest influence. Thus, from one point of view, the physiological data can be said to be "noisy," i.e., the signals of interest are buried in other signals which are more or less unrelated. Brainwave signals, for example, may contain some information about a person's state of consciousness, but they also are strongly influenced by sensory inputs, body movements, maintenance functions of the body, etc. Analytical procedures for separating the desired signals from the undesired noise are required for the detection and study of such physiological response patterns.

The simplest approach to this problem is averaging across many occasions. Schwartz (1976) applied this technique in his study of patterns of facial muscle tension levels and covert emotion. He recorded the envelope of EMG signals (electromyographic signals are closely related to muscle tension) from four facial muscles: the frontalis (the muscle in the forehead which controls lifting of the eyebrows, etc.), masseter (the jaw muscle), corrugator (a muscle which runs horizontally from eyebrow to eyebrow, under the frontalis), and the depressor (a muscle around the lips and mouth). Schwartz asked his subjects to imagine happiness, sadness, anger and a "typical day" in turn, after resting, baseline EMG levels were recorded. Although his subjects did not visibly change facial expression during this procedure, significant changes in average EMG levels were recorded.

EMG signals are made up of many brief impulses, and vary in intensity from moment to moment, despite no apparent change in expression, cognition or emotion. These changes may be considered to be noise for the purposes of identifying patterns associated with imagined emotions, and presumably vary randomly with respect to imagery. Schwartz's (1976) technique involved averaging EMG levels over a 30 second period of sustained imagery of each type. In this way, many of the undesired short term fluctuations in EMG level were averaged out, uncovering the significant differences in average EMG level associated with each imagined emotion.

Schwartz's results were encouraging. He found distinctive EMG patterns associated with the four imagined emotional states. It is interesting to note that the distinguishing features of these responses were in corrugator and depressor EMG levels, and not in frontalis or masseter EMG. Frontalis levels remained about the same in all states, suggesting another possible reason for the lack of correlation between subjective reports of relaxation and frontalis relaxation training (Brown, 1977). It may be that clinicians who have had success with "frontalis" EMG training for stress management were actually attaching the sensing electrodes low enough on the forehead to train for corrugator relaxation. Schwartz found corrugator relaxation to be typical of happy imagery, and excess corrugator tension was typical of sad imagery. High depressor EMG levels were typical of angry imagery. The "typical day" imagery produced responses similar to, but weaker than, the happy imagery.`

Although a few physiological responses are constant enough for a simple averaging approach to be of use, most responses are dynamic, constantly changing, and require more sophisticated techniques. Clynes' (1973, 1976) work with small finger movements is a good example of such a dynamic process. Clynes asked his subjects to imagine various emotions and express them through the movements of a finger, pressing on a bar. For each trial, in which an imagined emotion was expressed, he recorded the pattern of changing pressure on the bar, lasting about ten seconds.

The analytical problem for such data still involves separating the signal of interest, here a pattern of pressure varying with time, from finger pressure variations unrelated to the imagined emotion. Clynes collected many repeated responses from each subject and averaged them by use of a computer of averaged transients (CAT). This technique for averaging dynamic signals is used widely, and deserves description in detail.

Clynes recorded the names of various emotions on magnetic tape, at intervals. Each spoken emotion name, such as joy, anger, grief or love, was followed by a series of randomly spaced neutral signals, each sounding like a brief tap. Each tap was the signal for a finger response to be emitted. Clynes divided the pressure measurement of response to each emotion into many short time intervals, starting at the time of the signal from the tape recorder. The pressure during each time interval was constant enough to be reduced to a single sample value. For a single imagined emotion, Clynes collected a series of these samples at regular intervals following the signal from the tape recorder.

Clynes averaged each sample across many trials. In this way he produced an average set of samples, an average pattern of pressure variations with time. This averaging process produced a substantial improvement in signal-to-noise ratio. It may help to express it mathematically.

Call the first pressure sample in the first trial expressing an emotion P(1,1), the second sample of the first trial P(1,2) and the kth sample of the first trial P(1,k). Call the first sample of the second trial

P(2,1) and the first sample of the jth trial P(j,1). Call the first point of the average response pattern A(1), the second A(2) and the nth A(n). Then when averaging over t trials

$$A(n) = [P(1,n) + P(2,n) + ... + P(t,n)]/t$$

This averaging process can improve signal-to-noise ratio if the successive trials are time locked, i.e., if the response in successive trials begins at or near the same sample number each time, because the responses relevant to the signal will reinforce each other, while the random noise will average toward zero. For perfectly time locked signals, t trials will produce an average signal with a signal-to-noise ratio improvement equal to the square root of t (Cohen, 1974).

Clynes (1973, 1976) used this averaging process to construct average patterns or templates of pressure response for a series of emotions. He found that anger, grief, love, sex, joy and no emotion each had distinct response patterns which were similar across subjects. Love, for example, was expressed as a gentle curve, a pressure varying slowly with time, while anger was expressed as a sharp, brief impulse. It is interesting to note that he found these distinctive patterns to be similar for subjects from widely varying cultures, including Americans, Mexicans, Japanese and Balinese, although there were a few significant cultural differences. The Balinese had difficulty distinguishing anger from hate, while the Japanese did not, according to Clynes (1973).

The same CAT technique has been used by other researchers to look for weak patterns of physiological response. One widely used method is the study of evoked responses. In a typical experiment, a light is flashed in the subject's eyes repeatedly, at random intervals. Each flash of the light is considered to be a trial, and the EEG response to a number of flashes is averaged by CAT methods to yield an average visual evoked response (VER) pattern. The resulting average response pattern looks a little like a damped oscillation, if graphed with amplitude vs. time.

One researcher (Ertl, 1968a, 1968b, 1969, 1971, 1973) has reported that the period of time between the second and third peaks of the average visual evoked response is directly related to "neural efficiency" and IQ.

The intensity of stimulus, e.g., the brightness of the flash of light, in an evoked response experiment has an influence on the average evoked response pattern which is recorded. Buchsbaum and Silverman (1968) and Blacker, Jones, Stone and Pfefferbaum (1968) found that the pattern of variation of VER varied from subject to subject. They report that subjects who reduce the sizes of tactile judgements of width, in a separate tactile perception task, tend to show a decrease in amplitude of VER with increase of light intensity, while subjects who augment the sizes of tactile judgements tend to show larger VER for brighter light flashes. The same researchers report that schizophrenics and subjects under the influence of LSD show "reducing" response patterns, in which increasing light intensity produces decreasing VER size.

Clynes (1968, 1973) experimented with a variation of the usual VER procedure. Instead of using a simple flash of light, he flashed different patterns of lines and colors on a screen in front of his subjects. He found identifiable EEG VER patterns for different colors, and distinct responses for random dots, radial lines or polar coordinates.

John (1976) elaborated this procedure by studying VER to letters of the alphabet flashed on a screen. He recorded EEG from several scalp areas, including the occipital, parietal and temporal lobes. He found different VER patterns at all scalp locations for different letters of the alphabet, just as Clynes found different VER patters for different line drawings. When John studied the VER patterns for the same letter presented as two different shapes (e.g. lower case and capital letters), he still found different VER patterns in the occipital region, but the VER responses in the other scalp areas were similar for either shape.

John (1976) explained these results by pointing out that the occipital lobes of the cortex process visual information and should produce different responses for different shapes, while the other lobes of the cortex are involved in associational processes which derive meaning from the shapes, and the meaning of the upper and lower case letters is similar.

In a further elegant experiment, John (1976) found that a vertical line, which produces a consistent occipital VER pattern, elicits VER patterns in other cortical areas which are significantly different when the perceptual set is changed. Thus a vertical line seen as the digit "1" has a different meaning from the same pattern seen as the letter "L."

Pinneo and Hall (1975) used the CAT technique in a series of experiments which go far toward establishing the existence of useful correlations between physiological and psychological events. Their studies focussed on the physiological correlates of covert speech (verbal thinking), with the goal of testing the feasibility of communication from human to computer via EMG and EEG signals. Their studies proceeded in several phases. In the initial phase, they studied EMG and EEG waveforms correlated with overt speech (speaking aloud), and in the later phases the correlates of covert speech were studied. Pinneo and Hall expected to find similar patterns for both overt and covert speech.

In both the overt and covert speech phases, they ran training trials, in which template patterns were built up for each physiological measure and each word by having their subjects repeat each word, on command, several times. The data from successive repetitions were averaged by CAT techniques. Following a set of training trials were the recognition trials, in which a computer system attempted to identify words spoken or thought on command, by comparing them with the template patterns built up during the training phase.

In the overt speech trials, using a 15 word test vocabulary, 74% of the 5,400 trials were correctly classified using EMG responses alone, 63% were correctly classified by using EEG together with EMG to classify, and 34% were correctly classified by EEG alone. The method used by Pinneo and Hall for classification of responses, and for combining physiological measures for classification purposes was a very simple root-mean-square (RMS) distance measure, and as can be seen from the results above, this technique does not necessarily gain in accuracy if a combination of physiological measures are used for identification purposes. It will be worthwhile to consider how their classification procedure worked.

As in all CAT procedures, Pinneo and Hall recorded a collection of data samples for each trial. In these experiments, seven seconds of data were collected for each trial, and that seven second collection of data made up one epoch, or data block. There were seven channels of data recorded during each epoch: two EMG measures, four EEG measures and a single voice recording channel.

In the training phase, data from each of the six nonvocal channels were averaged, sample by sample, using the CAT technique, with a separate average template produced for each physiological measure and each word. The voice channel was used by Pinneo and Hall to time justify their data. The beginning of vocalization was detected in the voice recording, and all of the data were shifted forward or backwards until the beginning of vocalization occurred at the same sample number in every trial, thus ensuring perfect time lock for the averaging and the best possible improvement in signal-to-noise ratio. Thus, if vocalization began a bit early on one trial, before time justification, the sample numbers were adjusted upward to move the beginning of vocalization to the correct sample number.

A total of 255 samples made up a single epoch, but Pinneo and Hall had collected extra data points before and after vocalization. Only about 100 data points, centered around vocalization, actually contained useful data. Vocalization in one trial might begin at sample 112 and in another trial it might start at 136. Pinneo and Hall time justified their data by renumbering samples so that vocalization always began at sample 127. All of the useful information was then contained in samples 100 to 200, so the templates for each word were built up from these 100 data points. Call the first sample in the template for the first word T(100,1), the second sample of the first word T(101,1) and the last sample of the template for the first word T(200,1). After time justification, the first useful sample of an unknown word would be U(100), the second U(101) and so on.

In a recognition trial the RMS distance between the unknown word and each template was calculated and the unknown word was classified on the basis of the closest template. The RMS distance between template n and the unknown word was calculated as the square root of the sum of the squares of differences between successive samples, divided by the total number of samples:

$$D = (1/100)\left(\sum_{ii=100}^{200} (T(n,i) - U(i))^2 \right)^{1/2}$$

When several channels of physiological data were combined for classification purposes, Pinneo and Hall simply put them end-to-end, creating a single new template with more samples. When all six physiological channels were combined, a 600 sample template was created. Although this procedure for combining physiological measures was simple, it did not produce improvement in overall classification accuracy. More sophisticated techniques for approaching this problem will be discussed later.

Pinneo and Hall found that separate templates had to be produced for different subjects, i.e., different subjects had different patterns of physiological response associated with the pronunciation of the same word. They found the greatest intersubject variation in the EEG data and the most similarity in the EMG data. No particular EEG electrode placement was consistently found superior to any other placement.

The covert speech trials were run in a similar manner, except that the words were not spoken aloud, they were thought silently. A test vocabulary of five words was used. The results were disappointing without classifications were not much more accurate than chance expectation. They time justified the covert responses from physiological data, matching major features of the responses, and smoothed out all high frequency components in the EEG waveforms. The results of this processing were dramatic, the classification accuracy jumped from about 27% (compared to 34% for unsmoothed overt speech EEG data) to 62% for all EEG channels combined.

Pinneo and Hall found the EEG patterns for words to be very similar in covert and overt speech, though the patterns varied from subject to subject. Their findings may provides some experimental support for the behaviorist notion that verbal thinking is simply covert speech (Skinner, 1974).

The techniques for analyzing dynamic physiological processes which have been discussed up to this point are time-domain processes, they examine how the value of a measure changes from moment to moment. Frequency domain analytical procedures are also very useful, and deserve some explanation here. In frequency domain analysis, the signal to be analyzed is divided up into time segments called epochs, and each epoch is separately analyzed. The signals usually analyzed by this technique are those which vary rhythmically with time, such as EEG, and the frequency domain analysis focusses on the rate or frequency of the rhythms. A typical signal is complex, and can not be meaningfully analyzed as a single rhythmic frequency, so the usual procedure is to view it as the sum of several frequency components. The utility of frequency domain analysis of EEG is great in many applications because the most obvious and easily identified features of the brainwave signal are frequency components such as alpha waves, beta waves, etc.

The result of a frequency domain analysis is usually a spectral density function, which expresses the relative amount of power present at each frequency in the spectrum, or range of measured frequencies. A spectral peak at some frequency indicates that the signal contains a strong component at that frequency. One of the popular techniques for frequency domain analysis of signals is the Fourier transform. A commonly used implementation of the technique on modern computers is the fast Fourier transform, or FFT (Cooley, Lewis & Welch, 1977).

The use of the FFT requires making some assumptions about brainwaves which are not always justified. The main assumption is that FFT requires the waveform under analysis to be stationary, i.e., unchanging throughout time, except for rhythmic repetitions. Brainwaves are normally constantly changing, so this is not an accurate assumption. The errors from it become more serious as longer epochs are analyzed. Other errors from FFT become greater as epoch length shortens, so it is at best a compromise technique, but still a popular and useful one (Zetterberg, 1973).

Pinneo and Hall (1975) tried FFT analysis of their EEG and EMG data from overt speech trials, but the results were disappointing, so they did not pursue this line of research further.

Don (1975, 1978) used FFT analysis of a single channel of EEG in his research. He was working with graduate students in psychology who were practicing an introspective technique, "focusing." Focusing is similar to many Buddhist meditations, and is a quieting process designed to encourage insight. It involves stopping the internal dialogue while attending to bodily feelings. The students were trained in recognition of "felt shifts" which are precursors to insight.

Don's subjects practiced focusing while their brainwaves were recorded. They gave ongoing verbal reports of events in consciousness which were recorded on an audio tape recorder synchronized with the EEG recorder. Don analyzed the tape recorded EEG using FFT and very short epochs, 2.56 seconds long, so that a typical 45 minute session was broken up into 1024 epochs.

Don's (1975) hypothesis was that the EEG epochs recorded during insight experiences would be identifiable by FFT spectral patterns with peaks in the alpha frequency band and a corresponding subharmonic peak in theta. It is important to note that Don was not searching to learn what, if any, pattern of brainwave response correlated with insight. Instead, he set out to test a specific hypothetical pattern against his experimental data, a procedure which allows a simple pattern recognition approach. Don's hypothesis was based on earlier research (Green, Green & Walters, 1970; Morrell, 1966) in which simultaneous alpha and theta bursts were observed in raw EEG data.

Don's computer program for analyzing EEG data used a three step process in searching for epochs with the desired EEG pattern. First, each epoch was fast Fourier transformed. Then the alpha peaks in each spectrum, and the subharmonic peaks in theta and delta were identified in every epoch, and Z transformed across every epoch in each subject's data. The Z transforming process converted the absolute spectral density scores into relative scores which could be easily compared across subjects, despite intersubject variations in brainwave amplitude. Don was not concerned with the absolute size of any spectral peak, he simply wanted to identify peaks which were unusually large or small for each subject.

The third step of Don's analysis was pattern recognition. He rejected epochs with delta or beta peaks significantly above average, because a pilot study of his showed that such epochs might fit his pattern otherwise but would not match subjective reports of insight experiences. He then looked for large alpha peaks, together with successively smaller theta and delta peaks, and epochs with this pattern were selected as candidates for insight experiences. Although the computer picked more epochs as insight experiences than Don's subjects reported, the epochs which the computer picked as best fitting Don's pattern were in almost every case the same epochs identified by subjective reports of insight. Thus Don successfully demonstrated that a subtle event in consciousness could be recognized by EEG pattern analysis. He suggested (Don, 1975) that EEG biofeedback training might be done to enhance this pattern in the hope that more insight experiences would result.

Don's (1975, 1978) research indicates that pattern analysis in the EEG frequency domain can be useful in the recognition of events in consciousness. But it does not shed much light on pattern identification. A practical technique is needed for searching for and identifying interesting patterns of physiological response. Powerful pattern identification techniques are likely to make use of two related multivariate statistical techniques: principal components analysis and discriminant analysis.

Both of these techniques involve breaking the flow of data up into time segments, or epochs, each of which is independently analyzed. The results of analysis of an epoch typically consist of a collection of data, e.g., a set of FFT spectral density values for different frequency ranges, and each of these data may be considered as a separate variable. A useful way of thinking about the data from an epoch is as a single point in a mathematical multidimensional hyperspace (a hyperspace has more than three dimensions). The set of epochs of data resulting from an experiment can then be considered as a set of points in hyperspace. Similar physiological states would produce points close to each other in this space, and different physiological states would correspond to clusters of points separated from each other. Such a space could contain dimensions corresponding to more than just EEG data from a single electrode pair, it could also include other EEG data, EMG, skin temperature, GSR, BSR and other physiological data. Stoyva and Kamiya (1968) and Kamiya (1974) suggested that such a multidimensional approach to psychophysiology might lead to insights in the study of consciousness.

It is difficult to visualize a many dimensional hyperspace, and as the number of dimensions increases, it becomes an unwieldy task even for high speed computers. For this reason, special mathematical techniques have been developed for extracting most of the useful information from a high dimensional data set, while collapsing it to a smaller and more manageable number of dimensions.

Principal components analysis is a technique for constructing a new set of axes (variables) which are orthogonal (perpendicular) and aligned along the directions of maximum variance (scatter of data points in hyperspace). The first principal component is aligned in the direction of maximum variance, the second component is aligned in the direction, orthogonal to the first, which maximizes the remaining variance, the third principal component is orthogonal to the first two and aligned in the direction which maximizes the remaining variance, etc. It is usually possible to construct a set of principal components with fewer dimensions than the original set of variables which accounts for almost all of the variance in the original data (Morrison, 1967). This collapse in dimensionality can make further calculations, such as pattern identification or recognition, easier.

The usual method for calculating principal components involves the use of matrix algebra to create the principal components as linear combinations of the original variables. This is done by analysis of the eigenvalues (roots) of the covariance matrix of the original data set (Morrison, 1967).

Discriminant analysis is a related technique which operates on several groups of data points in hyperspace, corresponding to groups of epochs of data from different experimental conditions or states of consciousness. Consider a simple experiment in which two states of consciousness are studied. Two sets of physiological data are collected, one for each state of consciousness. The experimenter might hope that these two states of consciousness correspond to different physiological states. This would imply two separate swarms or groups of data points in hyperspace. The goal of discriminant analysis is to create a new set of axes in hyperspace which maximally separate the different experimental groups, while remaining orthogonal to each other. It is usually possible to achieve a substantial collapse in dimensionality with this technique, just as with principal components analysis, so that a small set of new variables, made up of linear combinations of the old variables, contains most of the discriminating power available. For two groups of data points, a single line in hyperspace will be the result, for three groups a hyperplane is the usual result and so on (Gnanadesikan, 1977).

The results of this type of discriminant analysis are called discriminant coordinates or CRIMCOORDS. They are calculated by eigenanalysis of the matrix product of the inverse of the within-groups covariance matrix and the between-groups covariance matrix (Gnanadesikan, 1977).

A closely related type of discriminant analysis can be used to create polynomial combinations of the original variables, which can be used to calculate the posterior probability that an unknown data point belongs to a particular group or cluster of points. Jennrich (1977) calls these equations group classification functions. The group classification function is a type of discriminant equation likely to be useful in physiological pattern recognition systems.

Discriminant analysis and cluster analysis are related techniques for classification. Unlike discriminant analysis, cluster analysis does not depend on a training data set with groups of data points of known group membership. Cluster analysis is a process by which groupings of points in hyperspace are discovered and identified.

Larsen, Ruspini, McNew, Walter and Adey (1973) studied the relative effectiveness of discriminant analysis, cluster analysis and classification of EEG sleep stages by human experts. Their experimental data consisted of EEG recordings from a single electrode pair on each of two chimpanzees.

For the purposes of this dissertation, the most interesting feature of the Larsen, et al. (1973) study is the use of principal components analysis and discriminant analysis to combine many physiological data and create a new, smaller set of variables with more discriminating power than any of the old variables.

Human EEG experts examined the raw EEG data, recorded on chart paper, and classified 100 epochs of the data into five sleep categories: drowsy, light, medium, deep and REM (rapid eye movement, and hence probably dreaming), based on a classification system developed by McNew, Kado, Howe, Zweizig and Adey (1968). About 20 epochs were classified in each of the five stages. These epochs were used as a training data set for later discriminant analysis. A second set of 100 epochs was classified by the human experts, for use as a test data set, to check the accuracy of classifications made after discriminant or cluster analysis.

Larsen, et al. (1973) used principal components analysis to reduce their 32 dimensional brainwave data to five new dimensions. Using these five new variables, a new data matrix was constructed for each of the five sleep stages from the 100 data points in the training data. Discriminant analysis was then performed, using the five dimensional training data, resulting in a set of discriminant coordinates.

The discriminant coordinates were used to plot and classify the second 100 data points. About 70% of the data points were correctly classified, with those that were misclassified lying rather far from any of the groups. This is a fairly high success rate, though it would be more impressive if the states of consciousness which the experiment sought to identify had been defined by some non-brainwave measure. Defining grouping by visual EEG analysis must increase the likelihood of success at sorting EEG signals into such groups automatically. Larsen, et al. (1973) suggested that the 30% of the data points which the computer failed to correctly classify were probably classified on the basis of contextual data when the human experts examined the chart records. The discriminant analysis considered each epoch as an independent event and did not take context into consideration.

Cluster analysis revealed two main clusters in the data points, roughly corresponding to synchronized and desynchronized EEG states. Larsen, et al. (1973) were disappointed in this result; they had hoped to find clusters roughly corresponding to the groupings identified by human analysts.

Problems to be solved in physiological data analysis

The studies reported above were successful in finding patterns of physiological response correlating with events in consciousness. They provide some encouragement for the belief that such correlates exist. Of course, there are studies in which such correlates were not found, e.g., the studies which unsuccessfully searched for the physiological correlates of hypnosis (Diamant, Dufek, Hoskovec, Kristof, Pekarek, Roth, & Velek, 1960; Fujisawa, Koga, & Toyoda, 1959).

But the absence of evidence of a correlation is not evidence of absence. It can simply be evidence that the analytical techniques in use are not adequate to find the correlation.

One basic problem is the identification of the states of consciousness by some independent means, apart from the physiological measures under study. Larsen, et al. Sidestepped this issue and defined their states physiologically. Most other investigators either rely on subjective reports, as did Don (1975), or on evoked responses, as did Pinneo and Hall (1975).

Another equally troublesome problem is the amorphous nature of events in consciousness. They vary in duration and intensity as well as in quality. It is difficult to define precisely the beginning or end of an event of interest and it probably is not possible to evoke events of many types, such as emotions, with predictable latency.

Time domain data analysis procedures, such as the CAT technique used by Pinneo and Hall (1975) depend on split second time justification, and depend on either predictable latency or an independent method of identifying the beginning of event of interest (e.g., the beginning of vocalization). This makes time domain procedures poor candidates for research in the correlates of many affective and cognitive states of interest. Frequency domain techniques are somewhat more promising because they are considerably less sensitive to precise timing. Don (1975), for example, succeeded in identifying a rather subtle event in consciousness despite imprecise timing information from his subject's reports.

If a pattern of physiological response correlated with an event of interest is identified, then the problem of analyzing ongoing (real-time) physiological data and comparing them with one or more stored patterns becomes important. This data analysis must be carried out rapidly enough so that it is completed before the next epoch is over, or else the system will fail to keep pace with the incoming data.

Most pattern detection schemes involve lengthy calculations which consume considerable computer time. These techniques work well enough when there is time available to analyze tape recorded data at leisure, off-line (on-line or real time analysis is done as data is collected, off-line analysis is done later, from recorded data). A practical biofeedback system for learning control of events in consciousness will have to use real-time, on-line analytical procedures. Larsen, et al. (1975), Don (1975) and Pinneo and Hall (1975) all used off-line analysis. Pinneo and Hall did attempt a series of on-line trials, but obtained success rates considerably lower than in off-line trials.

FFT, the most popular frequency domain analytical method, has some pitfalls of its own. It consumes considerable computer time, despite improvements in the technique which maximize its speed (Cooley, Lewis & Welch, 1977). It depends on the use of a predetermined, fixed epoch length, which is not easily adapted to the ephemeral nature of events in consciousness, and it involves making assumptions about the statistical properties of brainwaves which may not always be justified.

Pattern biofeedback

If all of the problems of physiological pattern detection and identification are solved, the next step in using them for teaching voluntary control of consciousness will be to do pattern biofeedback training. It seems prudent to examine the literature on previous attempts at training for control of patterns of physiological response, both to see if it can be done, and to learn if such training is likely to lead to the desired voluntary control over events in consciousness.

Green and Green (1977) trained subjects in forearm muscle relaxation (with EMG training), handwarming (with skin temperature training) and eyes-open occipital alpha production (EEG training). They then asked their subjects to attempt to control all three physiological processes at the same time, providing visual feedback with three vertical bars of light, one for each modality. Although this "triple training" task was reported as more difficult by the subjects, several were able to demonstrate control over all three responses. It may be that part of the difficulty of the task arose from the three feedback signals; a single combined feedback signal might have been easier to learn from.

Peper (1972) found that brainwave control at two independent scalp locations could be learned through biofeedback training, and he suggested that such training might be useful in the mapping and study of states of consciousness. Weber and Fehmi (1974) went on to demonstrate EEG training at five scalp locations.

Schwartz (1976) demonstrated combined training of pairs of responses. Heart rate and blood pressure were independently raised and lowered in one experiment, while EEG alpha and heart rate were independently controlled in another experiment. Suter, Francoli, Johnson and Smith (1977) demonstrated combined independent training of EEG alpha and skin conductance, and Rugh (1977) demonstrated EMG training of two independent muscle groups at the same time.

Webb (1977) used multiple channel EMG feedback in an innovative training procedure which taught blind subjects how to express their emotions with appropriate facial expressions. Three muscle groups were monitored: the zygomaticus (a muscle near the corners of the mouth), corrugator and frontalis. The zygomaticus was used in smiling to express happiness, the corrugator in frowning to express anger and the frontalis was used in raising eyebrows to express surprise. Each muscle controlled a feedback tone, and the blind subjects learned to control all three tones simultaneously. Webb's subjects did learn improved control over facial expression through this feedback training, though it is interesting to note that local training effects cropped up. All of her subjects had difficulty in controlling corrugator tension to express anger without tensing several other unmonitored muscles, thus producing an undesired facial expression. The use of more EMG channels would probably have reduced this problem.

There are two studies of biofeedback systematic desensitization of drug addicts which are relevant to both the pattern biofeedack question and to the question of biofeedback and volition. Systematic desensitization (Wolpe, 1973) is usually used for treating phobias. The procedure involves the construction of a hierarchy of images which range from relaxing to very threatening. The patient is taught a relaxation procedure, and then is asked to begin imagining items in the hierarchy, beginning with the most relaxing. As soon as anxiety is noted, the procedure is stopped, and a more relaxing image is imagined until relaxation is re-established. Then the steps up the hierarchy are resumed. By this process, the patient eventually learns to imagine previously threatening images while remaining relaxed. The theoretical basis for this procedure is the idea of reciprocal inhibition, which states that it is very difficult to be aroused or anxious and relaxed at the same time. The presence of one state inhibits the other.

Lebow and Allen (1974), working at Lompoc Federal Prison in a drug rehabilitation program, adapted this procedure for use with drug addicts. Their idea was to desensitize the arousal stimulated by drug-related images by a procedure similar to that used for phobias. A hierarchy of images was assembled on color transparencies (slides), ranging from neutral to slides of heroin purchase and use. They used galvanic skin response (GSR) to measure arousal, and constructed an automatic slide projector controller which could advance or reverse the slides on command from a timer and from the GSR instrument.

The projector would advance from one slide to the next at regular intervals, as long as no GSR response was detected, but would reverse to earlier slides if a GSR response was elicited. Thus it was not possible for a subject to view the entire set of slides unless each of them could be viewed without GSR response.

Lebow and Allen's patients were men who had committed crimes such as bank robbery, but who had pled that they had lost control of their volition due to drug addiction, and that they were not responsible for their behavior. The goal of the treatment program was to restore volition to these men, to teach them to modify their responses to drug-related stimuli so that they were no longer uncontrollable.

Lebow and Allen found that non-addicts had little difficulty with this task, but that heroin addicts needed extensive training to succeed at it. They were encouraged by this result, and by subjective reports from their patients, who said that their previously uncontrollable desire for drugs was diminished and controllable. But they found that some addicts did not experience diminished desire for heroin, and that these men exhibited a sharp drop in fingertip temperature when watching the slide show while suppressing GSR responses. Lebow and Allen hypothesized that these men had learned to suppress GSR responses without relaxing, and they interpreted the drop in skin temperature as a stress response associated with this process.

In my work (Scully, 1977) at Gladman Hospital, in Oakland, California, I experimented with a pattern biofeedback system based on Lebow and Allen's observations. The system consisted of a slide projector controlled by skin temperature and GSR responses. Slides advanced at regular intervals until a GSR response or a skin temperature decrease was noted. A GSR response caused the projector to back up three slides and stop until the response stopped. A skin temperature decrease stopped the projector until the temperature increased again. Although this system was only tested with a few addicts in a pilot study, the results were promising. The dual modality system was more sensitive to mood changes than a single modality. Addicts reported that this improved sensitivity was helpful in their training.

The studies described above provide evidence that pattern biofeedback is possible, at least for simple patterns. There is less evidence available regarding the effectiveness of such training in teaching voluntary control over specific events in consciousness.

The brainwave studies in which alpha enhancement training was attempted in an effort to achieve a meditative state of consciousness are probably the best examples of work in this area. The physiological monitoring studies of some types of meditators revealed phase coherent alpha waves which spread from the back to the front of the scalp in both hemispheres (Banquet, 1972). Phase coherence means a stable phase relationship between waves from different scalp areas (i.e., the waves from different areas were of the same frequency). Some early reports of occipital alpha enhancement biofeedback training were similar to the subjective reports of meditators (Kamiya, 1969), i.e., inner calm and peace. But later experiments in alpha training led to the controversy discussed earlier; some investigators did not obtain subjective reports similar to those of meditators.

Two channel EEG training for interhemispheric phase synchronous occipital alpha has been done by several investigators (Mayo, Targ, & Hurt, 1975; Mikuriya, 1977). Successful subjects report profound feelings of peacefulness during periods of phase synchronization (synchronization means maintaining near zero phase angle between waves from different scalp areas).

The evidence for an improvement in the correlation between peaceful states of consciousness and bilateral alpha synchronization training, compared to single channel training, is still inconclusive, but does point in the desired direction. On intuitive grounds, it seems reasonable that training for a more precisely defined physiological state may lead to less variation in subjective reports.

Neurophysiology, Transactional Analysis and the Ego State Inventory

Differences in emotional tone are among the most distinctive features of the identity states selected for study in this research. These states will be discussed in more detail later, but first a brief discussion of the neurophysiology of emotions is in order.

The neurophysiology of emotion

There are many possible physiological measures, from different parts of the nervous system, which could be analyzed in a search for the correlates of emotion. The nervous system is divided into three major sections, somatic, autonomic and central. The nerves to and from the sensory and motor organs make up the somatic nervous system. Schwartz's (1976) facial EMG data are the best example of emotion-somatic correlation.

The autonomic nervous system is in turn divided into the sympathetic and parasympathetic divisions. The autonomic nervous system responds strongly to many emotions, but it may be difficult to identify the specific emotion from autonomic data, which seems to vary mainly along an arousal-relaxation dimension. The difference between sympathetic and parasympathetic arousal may in some cases indicate an emotional polarity. Skin temperature and electrodermal phenomena are primarily autonomic nervous system measures. GSR can be triggered by the orienting response or almost any arousing stimulus, regardless of emotional type or polarity (Darrow, 1927), while skin temperature changes are somewhat less sensitive to orienting and more sensitive to the polarity of arousal, with negative emotions (e.g., fear and anger) reducing temperature, and positive emotions or relaxation allowing it to rise.

The central nervous system is more likely to be a source of physiological data which can make fine distinctions among emotional states. This system can be divided into three main sections, the hindbrain (spinal cord, medulla and pons), midbrain and forebrain. The first two parts have been called the neural chassis (Mclean, 1973), and can manage the basic tasks of reproduction and self-preservation. These parts make up almost the entire nervous system of a fish or amphibian. Reptiles have some forebrain in addition to the neural chassis, and this first layer of the forebrain has been called the R complex (MacLean, 1973).

Humans have two additional layers of forebrain, the limbic system and the neocortex. It is these two layers which contain the higher mental processes. The limbic system has been called the emotional brain and is often considered to be the link between the emotions and the body (Green & Green, 1977; MacLean, 1973). The limbic system controls much of the autonomic nervous system. This control is accomplished through the hypothalamus, thalamus and pituitary gland, which are parts of the forebrain. Electrical or chemical stimulation of specific tiny portions of the thalamus or hypothalamus can trigger strong and specific emotional responses (Wooldridge, 1963).

The cerebral cortex is the topmost layer of the brain, and is the part of the nervous system which is most highly developed in human beings. It is cortical development which distinguishes humans from the lower animals, and the cortex is clearly the seat of most higher mental abilities. The cortex and limbic system, including the thalamus, are, of course, intimately interconnected. Because the cortex is closest to the scalp, most of the electrical activity recorded from the scalp (EEG) is cortical in origin, even though the activity may be a response to deeper, especially thalamic, activity.

Can scalp EEG yield information about emotions? This is one of the questions which the experimental portion of this dissertation addresses. There is experimental evidence that the cortex exchanges signals with the limbic system and midbrain, and that these signals are relevant to emotions. The work of Penfield, a neurosurgeon, provides some excellent evidence.

Penfield (1952, 1959) operated on patients with severe epileptic seizures. He removed a portion of the skull, under local anesthetic, and electrically stimulated the exposed cortex, to locate the diseased portion so that it could be surgically removed. He obtained subjective reports from his patients of their experience during this painless electrical stimulation of the brain. Surprisingly, he found that such stimulation, especially in the temporal region, often caused his patients to relive a vivid past experience, with sights, sounds and emotions. Penfield (1952) reported:

> Under the compelling influence of the stimulating electrode, a familiar experience appears in a patient's consciousness whether he desires to focus his attention upon it or not. A song goes through his mind, probably as he heard it on a certain occasion; he finds himself a part of a specific situation, which progresses and evolves just as in the original situation. It is, to him, the act of a familiar play, and he is himself both an actor and the audience.
>
> The subject feels again the emotion which the situation originally produced in him, and he is aware of the same interpretations, true or false, which he himself gave to the experience in the first place. Thus, evoked recollection is not the exact photographic or phonographic reproduction of past scenes and events. It is reproduction of what the patient saw and heard and felt and understood. (p.183)

Penfield's report indicates the existence of at least a one-way connection from cortex to emotion. There are other data which provide some evidence of an emotion to cortex connection.

Walter (1963) reports that young children exhibit more four to seven Hertz brainwave activity than adults. These signals were first observed as a distinct pattern in studies of the thalamus, and came to be called theta waves. Theta scalp EEG can be elicited in many children by frustration and other emotions, according to Walter. With suitable emotional stimulation, Walter succeeded in eliciting emotion-related theta from normal adults. He reported that ill-tempered adults produce more theta than even-tempered subjects.

EEG signals in the four to eight Hertz range are also associated with other events in consciousness. Drowsiness often elicits theta, for example. Thus, it seems that the task of relating brainwaves to emotional events will not be an easy one. The electrical activity which can be recorded from the scalp is the sum of signals from many sources; some of the signals have to do with sensory data, some have to do with the maintenance functions of the body and some seem related to events in consciousness. The use of pattern recognition techniques may help to reveal the patterns of interest, which are buried in unrelated "noise."

Transactional analysis

One of the difficulties in studying identity states is the objective identification of them. Physiological pattern recognition techniques may soon help with this task, but before that stage is reached, another means is required for judging the presence or absence of an identity state, so that the physiological pattern associated with it can be identified, if it exists.

The identity states chosen for study in this research were selected because they are defined behaviorally and can be identified by an objective observer. They are not necessarily the most useful or interesting states for study, rather they are simple to identify. These states are functional egostates as defined by transactional analysis (Berne, 1961; Dusay, 1977a, 1977b).

Transactional analysis (TA) is a theory of personality and a school of psychotherapy founded by Eric Berne (1961), and based in part on Wilder Penfield's (1952) work. Berne observed that people sometimes act as if they were small children, at other times they act as adults, and at still other times, they behave as parents, critical or nurturing. Berne (1961) called these different personality fragments "ego states" and said:

> An ego state may be described phenomenologically as a coherent system of feelings related to a given subject, and operationally as a set of coherent behavior patterns; or pragmatically, as a system of feelings which motivates a related set of behavior patterns. Penfield has demonstrated that in epileptic subjects memories are retained in their natural form as ego states. By direct electrical stimulation of the bared temporal cortex of either side, he was able to evoke these phenomena. (p.xvii)

Berne's structural theory defined three types of ego states, Parent, Adult and Child, and identified behavioral characteristics typical of each. The Parent is nurturing or critical, and feeds, comforts, limits or prohibits. The Adult computes information, it is objective, businesslike and organized. The Child may rebel with fighting and defiance, or be compliant and adaptive, or it may be spontaneous, imaginative and natural.

Dusay (1977a, 1977b) continued the development of this theory after Berne's death in 1970, and evolved a theory in which five "functional egostates" are defined by observable behaviors. He began using egograms, charts of the relative strength of each of the five functional egostates, in therapy and found that trained observers agreed in identifying egostates and constructing egograms. He listed the five states as: Critical Parent, Nurturing Parent, Adult, Free Child and Adapted Child.

The theraputic aspects of TA are not relevant to the subject of this dissertation. It is Berne's theory of personality and behavior which is of interest here.

The overt manifestations of social intercourse are called transactions, and Berne analyzed these as interactions among the participant's ego states. He also analyzed repeating patterns of transactions, which frequently occur, as pastimes, psychological games, etc. Identification of the physiological correlates of activities such as these would open up interesting possibilities for biofeedback training. I expect to eventually experiment in this area, perhaps using psychodrama to evoke the desired behavior pattern, while physiological data is collected and analyzed. This dissertation concerns itself with a simpler study in which egostates are operationally defined by subjects' responses to a test.

The Ego State Inventory

McCarley (1974) developed a test, the Ego State Inventory, which is designed to evoke and identify functional egostates and construct egograms. The test consists of 52 cartoons. Each cartoon depicts two people interacting in a situation, with the first person supplying an Adult stimulus and the second person having five possible responses. McCarley designed the test as a paper and pencil multiple choice test, in which the subject is asked to imagine what response the second person would make. The five responses correspond to the following states (McCarley, 1974):

> 1. The Punative Parent (PP) is a subdivision of the Parent ego state and contains a huge collection of "no's," "don'ts" and admonitions. This is the center of the rigidly internalized data which comes from authority. This kind of Parent is seen as non-rational, prejudiced, arbitrary and usually prohibitive.
>
> 2. The Nurturing Parent (NP), which has sometimes been equated with the "Good Parent," is often seen in supportive or sympathizing behavior.
>
> 3. The Adult (A) is a data processing computer in the individual that estimates probabilities about reality which are essential for him to interact effectively with his environment. Old data is [sic] checked out in the light of new information and then updated or discarded. It is the part of the individual which calculates solutions to problems.
>
> 4. The Rebellious Child (RC) is the impulsive, assertive and self-indulgent part of the personality. It is expressed as a resentment of authority and a lack of concern for the rights of others.
>
> 5. The Adaptive Child (AC) is formed by the influence of parental demands. Compliant and withdrawal behaviors are common. (p.3)

McCarley's five egostates are different from Dusay's in one critical area. McCarley substituted the Rebellious Child for Dusay's Free Child. This is an incongruity in his test from a TA point of view, but it does not seriously impair its usefulness as a means of evoking and identifying identity states in a search for their physiological correlates.

McCarley administered his test to several groups of subjects. He found, as expected, that Roman Catholic nuns scored very high on Nurturing Parent, computer programmers scored high on Adult, and juvenile delinquents scored highest on Rebellious Child. He found test-retest correlation coefficients ranging from .47 for the Rebellious Child state to .73 for the Punitive Parent egostate.

Slides (transparencies) of McCarley's cartoons were made for use in the experiment described in chapter 2. The cartoons are reprinted in Appendix A. Presentation of these slides to the subjects in this study was controlled by a computer which also collected and analyzed physiological data.

Hardware Development

Consider for a few moments what an ideal biofeedback system might be like. It should be inexpensive and portable. It should be adaptable to detecting and training any desired pattern of physiological response, and it should be capable of providing feedback in many modes. The power and flexibility of computers suggests that the ideal biofeedback system should be computerized.

This dissertation describes the first few steps toward the development of such a system, together with a study which tests the effectiveness of the system in identifying patterns of physiological response. The study also tests the hypothesis that identifiable patterns of physiological response exist, which are associated with specific identity states.

Advances in microelectronics in the last generation have produced a series of breakthroughs in computer technology. Computer systems which once filled vast rooms and cost millions of dollars have shrunk to breadbox size and cost about a thousand dollars.

This new technology makes it possible to build a portable computer system for collecting and analyzing physiological data using large scale integrated circuits. Large scale integrated circuits are electronic devices a few centimeters long which contain thousands of active elements, such as transistors, each of which can perform amplifying or logical operations. One type of large scale integrated circuit is the microprocessor chip. Integrated circuits are commonly called chips because they are fabricated from thin slices or chips of silicon. A microprocessor chip such as the Intel Corporation's 8080A can perform arithmetic and logical operations at high speed, under the control of a program, a set of instructions stored in external program memory. Such chips now cost about $25.

A computer system built around a microprocessor chip is usually arranged as a group of printed circuit boards (or cards as they are often called) which plug into a common mother board. The mother board interconnects the individual cards with a pattern of conductive lines which are collectively called a bus. Cards which plug into the bus may include a central processing unit where the microprocessor chip resides, memory cards where instructions and data are stored, and interface cards which make it possible for the computer to exchange data with the outside world through peripheral devices (e.g., physiological data collection equipment, a keyboard, printer or cathode ray tube and a magnetic tape recorder for external data storage).

Data are communicated and stored in binary form, with 1's and 0's represented by voltages which are either high or low. A single binary digit is a bit, while a group of eight binary bits is called a byte. A byte of data might represent an alphanumeric character or a number ranging from zero to 255. Data expressed in binary numbers are called digital data, and the process of converting data from physiological measurements into binary form is known as digitizing.

The low cost of microelectronic components has led to the development of inexpensive computer systems for educational and personal use. Several companies, including MITS, IMS Associates and Polymorphic Systems Incorporated, have been marketing micro computer systems designed around the Intel 8080A chip. These systems share a common bus design in which a mother board with 100 pin sockets is used to interconnect circuit cards, and circuit cards made by different manufacturers can be used in the same computer system by plugging them into the standard "S-100 bus." The bus provides power supply voltages to operate the plug-in cards, and has specific interconnections assigned to data, address and control signal exchange among the cards.

An 8080A microcomputer system was designed and built for this research, beginning in 1974. Although the original prototype system did not use the S-100 bus, because its construction was begun before the S-100 bus became popular, the system has since been redesigned with S-100 bus architecture. The unique physiological data interface cards designed for this study are therefore compatible with thousands of existing computer systems.

Before a computer can be used to analyze physiological data, the data have to be collected from the human body, amplified, filtered, digitized and communicated to the computer. Most computer systems are powered from the 110 volt line, and consideration must be given to electrical shock protection for subjects. If EEG and EMG signals are to be monitored, these weak signals may be buried in 60 Hz power line interference unless the subject is grounded, shielded or unless some isolation is provided.

The system for this research was designed with all physiological monitoring circuitry powered from a single rechargable battery. DC/DC converters were used to produce the assorted power supply voltages required. All data going to the computer were optically isolated. An optical isolator converts an electrical signal into a beam of light whose brightness varies as the signal varies. This light shines onto a phototransistor which converts the optical signal back into an electrical signal.

The system was designed to monitor skin temperature, skin resistance (GSR/BSR), muscle tension (EMG) and two channels of brainwaves (EEG).

Non-EEG data collection techniques

Skin temperature was measured with a thermistor probe. A thermistor is a resistor with a negative temperature coefficient. Its resistance decreases with increasing temperature. The probe selected (Yellow Springs Instrument #44007) was chosen for its very low mass. The speed with which a thermistor can respond to temperature changes increases with decreasing mass due to decreased thermal inertia. A bridge circuit, balanced with a ten turn helipot, and an amplifier were used to convert temperature changes into voltage changes.

Even with a low mass thermistor probe, the skin temperature signal is a slowly changing voltage. Optical isolators exhibit some drift in transmission gain due to aging and temperature changes, and a simple optical isolator is unsuitable for isolating DC or slowly changing signals because this drift will introduce errors. One solution to this problem is to convert the DC or slowly changing voltage into an AC (or oscillating) signal of high enough frequency to avoid drift problems.

A voltage controlled oscillator (VCO) module was designed to handle this task. The module accepts an input voltage and converts it into an output whose frequency is directly proportional to the input voltage with a linearity error of 0.1%. For skin temperature, the VCO was adjusted to accept an input voltage ranging from -5 to +5 volts with output frequencies ranging from 2 kHz to 48 kHz (kHz is an abbreviation for kiloHertz, or thousands of cycles per second). These correspond to temperatures ranging from five degrees Celsius below baseline to five degrees above the baseline temperature.

The output from the VCO circuit was optically isolated and then fed to a 12 bit binary counter. Such a counter can count up to 4095 before it overflows. This counter was allowed to count the VCO output for 1/12 second, and the resulting total was then automatically transferred to a buffer latch (memory) so that it would be available for the computer to pick up. This total number of counts ranged from 200 to nearly 4000 for the ten degree Celsius temperature range covered by the system, and temperature changes as small as 1/100 of a degree Celsius could be resolved.

The advantages of this system of VCO, optical isolator and counter are that the problems of drift in the optical isolator and of digitizing the data for the computer are both solved at the same time. The same scheme was used to handle all of the other slowly changing physiological data. A fringe benefit of this approach to digitizing is that 1/12 second averages are automatically generated by the system, thus smoothing any rapid fluctuations in the data.

Skin resistance was measured by the constant current method, by putting the subject into the feedback loop of an operational amplifier, with a sensing current of six microamps, using 13 mm (1/2 inch) diameter silver electrodes held in place with velcro elastic fingerbands. Basal skin resistance (BSR) was measured as a voltage directly proportional to skin resistance. This signal was fed to a VCO whose output range was zero to 36 kHz, giving a range of zero to 3000 counts per 1/12 second, corresponding to a range from zero to 3000 kohms. An optical isolator was used between the VCO and the counter.

An analog logarithmic amplifier was used to create a voltage proportional to log BSR. This signal was differentiated with a time constant of two seconds to produce a galvanic skin response (GSR) signal proportional to the rate of change of log BSR. The GSR signal, ranging from -5 to +5 volts, fed another VCO which in turn was optically isolated and counted by another 12 bit counter. Zero GSR (constant skin resistance) produced about 2000 counts per 1/12 second, an increasing skin resistance lowered this count and a GSR response (decreasing skin resistance) raised it. A step change in resistance 100 kohms from 115 kohms changed the count from 2000 to 4000. The resolution of the GSR data was 130 counts per kohm of step resistance change.

Electromyographic (EMG) signals were picked up by 13 mm (1/2 inch) diameter silver surface electrodes which fed a differential amplifier with a bandpass from 90 to 500 Hz. The amplified EMG signal was rectified and averaged by an RC circuit with a time constant of .1 second. The resulting average EMG signal was fed to another VCO, optically isolated and counted by a fourth counter. The count for 1/12 second ranged from zero to 2000 counts for EMG levels from zero to 40 microvolts RMS, giving a resolution of 50 counts per microvolt.

The counter chains described above were eventually incorporated on a single S-100 compatible plug-in printed circuit card, along with their associated buffer latches, timing and control circuitry. Five complete counters are on the final version of this circuit card, allowing for an additional EMG channel. The voltage controlled oscillators and optical isolators were located next to the physiological data amplifiers, on a separate chassis.

The counter chain card contained a 12 Hz timing signal generator, derived from the 60 Hz power line frequency, and this circuit transmitted an interrupt signal to the computer's CPU once every 1/12 second, to signal that data was waiting in the buffer latches. Thus the computer picked up fresh skin temperature, EMG and GSR/BSR data 12 times a second.

Brainwave data collection and analysis

The method chosen for analyzing brainwave data deserves special consideration and discussion because of its importance. I believed that brainwave data were most likely to contain detailed information about identity states, and hence chose a brainwave analysis approach with care.

The problem of identifying physiological response patterns associated with events in consciousness may be thought of as the problem of decoding the body's language. This metaphor leads easily to looking at the considerable literature which has developed on the recognition of vocal speech patterns, a related problem. In the time domain, human vocal speech is a high data rate (rapidly changing) signal which is difficult to analyze. Speech sounds vary considerably from person to person and from time to time, even though the same word is repeated (Georgiou, 1978). The traditional approach to this problem has been to extract a few useful "features" of the speech signal. Features are slowly varying parameters, such as average amplitude, extracted from the raw data.

The features extracted in speech analysis are usually from the frequency domain, just as in brainwave analysis. Although frequency domain analysis is sometimes done by FFT, the problems of FFT in brainwave analysis also crop up in speech analysis. An alternative frequency domain feature extraction approach is zero crossing detection and amplitude-period analysis (Georgiou, 1978). Some speech recognition systems use this approach together with multiple bandpass filters (an idea which will be discussed again in chapter 5, in a discussion of improvements which could be made in future studies).

To understand zero crossing detectors, recall that the signals with which we are concerned are wavelike, they constantly vary. If any steady (DC or direct current) component is eliminated, the signal varies up and down around zero. A zero crossing detector identifies the points at which the signal passes through zero, on its way up or down, as it must twice each cycle. The period of time between zero crossings is obviously closely related to the frequency of a monochromatic signal (one containing only one frequency component). If the signal is greatly amplified before zero crossing detection, then the period between zero crossings will be related to the dominant frequency in any mixture of frequencies. This property of detecting the dominant signal is sometimes called "capture" and has both advantages and disadvantages. The advantage is that it can separate a dominant signal from rather strong competing signals, but the disadvantage is that information about the weaker signals is lost. A major and significant advantage of zero crossing analysis is that it is fast and well suited to real-time applications. It is also easily adaptable to varying epoch durations.

Beatty and Figueroa (1974) compared the effectiveness of FFT and amplitude-period measuring zero crossing analysis of brainwaves. Zero crossing detection measured the period of the waveform, and the RMS average amplitude of the signal between zero crossings was also measured. The dominant frequency is the reciprocal of the period between every second zero crossing. They looked at the average amplitude in six broad frequency bands and found correlations between the two techniques of about .80. That correlation is high enough to indicate that amplitude-period analysis yields a fair estimate of the spectral density of human EEG, at least in limited frequency bands.

The computer system for this research monitored two channels of EEG. Scalp signals were picked up by five millimeter diameter silver cup electrodes, and fed to differential preamplifiers with frequency response from three to 30 Hz. The sensitivity of the amplifiers to signals below three Hz was reduced to minimize the capture effect (by which low frequency signals could block the measurement of higher frequency, weaker, signals). The response at two Hz was less than 25% of the peak sensitivity. The response above 30 Hz was controlled to minimize 60 Hz and EMG interference, and the response at 40 Hz was less than 25% of the peak sensitivity. The two preamplifiers were carefully matched in phase and frequency response by hand-trimming capacitor values. Phase response was matched to within 10 degrees and frequency response was matched to five percent from three to 30 Hz.

Each amplified EEG signal was optically isolated (optical isolators can handle signals above three hertz without serious drift) and fed a zero crossing detector and a precision rectifier circuit. The zero crossing detector produced a brief pulse at every zero crossing of the EEG signal, i.e., at the beginning of every half cycle of the signal. This pulse was used to interrupt the CPU and inform it that an EEG half cycle had begun and that the EEG analysis circuitry required service.

The EEG analysis circuitry for one channel of EEG consisted of a timer which measured the period between zero crossings in 1/2000ths of a second, and a peak reading analog to digital converter which digitized the peak amplitude attained by the rectified EEG signal between each pair of zero crossings. At the beginning of each half cycle the computer was programmed to pick up the period and amplitude data from the previous half cycle and to reset the timer and amplitude circuitry so that data collection for the next half cycle could begin. The time data from the second EEG channel was also sampled so that the phase angle between the two channels could be calculated. This circuitry is discussed in more detail by Scully (1976a).

In the final system, the EEG preamplifiers and optical isolators were mounted in the same chassis with the other battery powered physiological data acquisition circuitry, while the rest of the EEG analysis circuitry for both channels of EEG was located on a single S-100 compatible plug-in printed circuit card.

An S-100 compatible interface card was designed which allowed the computer to control a Kodak Carousel slide projector. The projector lamp could be turned on or off and the tray of slides could be advanced to a new slide or reversed to an earlier slide, all under program control.

The computer was equipped with an ASR-33 Teletype, which was used as a printer, and a video interface which allowed the computer to put 16 lines of 64 alphanumeric characters onto a television screen. A free-standing keyboard, separate from the Teletype, was also interfaced with the computer, allowing the experimenter to enter instructions and data into the computer without the noise of the Teletype interfering with the experiment. The Teletype was located in another building, separate from the experimental area.

The computer had 64k bytes of random access memory. This was sufficient memory to store all of the data collected during a single experimental session. The system had the capability of recording digital data onto audio cassette tapes, so that data from each experimental session could be preserved for further analysis and read back into memory at a later date.

Chapter 2

METHOD

Subjects

Subjects in this study were volunteers from the Albion, Mendocino and Fort Bragg, California communities. It was planned that each subject would be his or her own control, in that each subject would view and respond to all of the slides, so no special subject selection procedures were used. The subjects ranged in age from 19 to 64 years, two were male and 10 were female. Nine of the 12 subjects had prior experience with biofeedback equipment (many were employees of Aquarius Electronics, a biofeedback instrument manufacturing company).

A modification was made in the data collection procedure after eight subjects had participated in the study. Two of the subjects who participated in the modified study were male and two were female. They ranged in age from 30 to 62 years.

Apparatus

The computerized physiological monitoring system described in chapter 1 was used to collect data. Inputs to the computer included GSR/BSR, EMG, skin temperature, two channels of EEG, and data from five pushbuttons. The five pushbuttons corresponded to the five possible responses a subject could choose for each cartoon in McCarley's (1974) test. Only a single pushbutton response was accepted from each subject for each cartoon.

McCarley's (1974) cartoon test items were photographed and turned into slides. Of the 52 cartoons, 49 were used as test slides and three were discarded because the cartoons were photographed poorly. The slides were placed in a Kodak Carousel slide tray, in the same sequence used in McCarley's test booklet (see copies of the cartoons in Appendix A). The discarded cartoons were numbers 37, 38 and 44.

A Kodak Carousel slide projector was connected to the computer, under its control. The slide projector and physiological data acquisition circuitry were in one room, where the subjects sat in a reclining chair during the experiment. I was with the computer in an adjoining room. The computer was equipped with a video monitor (television display) which allowed me to monitor the physiological data collected as the experiment progressed.

Procedure

The data were collected in January and February 1977. The study was run in my home. Subjects sat in the living room, with the slide projector and physiological data acquisition system, while the computer and I were in the adjoining bedroom during the data acquistion phase of the study. Both rooms were normally illuminated. The reclining chair used by the subjects was located about eight feet from the projection screen for the slides. The screen was moved closer for one myopic subject.

When a subject arrived to participate in the study, I invited him or her to sit in a reclining chair, located in the living room. I explained that the purpose of the study was to identify the physiological correlates of emotional states. As each physiological modality was connected to the subject, its purpose was explained, and questions were answered freely. It was made clear to each subject that the instruments were passive monitors. Verbal informed consent was obtained from each subject. The orientation and hook-up procedure took about 30 minutes for each subject.

The common ground electrode for all EEG and EMG measurements was a five millimeter diameter silver cup, placed on the tip of the nose, and held in place with tape. As with all other electrodes, the skin was prepared by scrubbing lightly with a Scotchbrite pad and cleaning with rubbing alcohol. Bentonite electrode paste (Taylor & Abraham, 1969) was used for this ground electrode and for the other EEG electrodes. EKG-sol electrode cream was used for the EMG electrodes. The reference for the two monopolar EEG measurements was created by linking two five millimeter diameter silver cup electrodes, one on each mastoid process.

For nine subjects, the two active EEG electrodes were placed temporally at T3 and T4 in the 10-20 system (Jasper, 1958). For the other three subjects, these electrodes were placed occipitally at O1 and O2. In all cases, these two electrodes were held in place with a velcro elastic headband. The ground and reference electrodes were held in place with 13 millimeter (half inch) wide tape.

For five subjects the EMG electrodes were placed over the frontalis muscle at Fp1 and Fp2 in the 10-20 system, and for these subjects the electrodes were held in place by the same elastic band which retained the EEG electrodes. The EMG electrodes were 13 millimeter (half inch) diamater flat silver disks. For seven subjects the EMG electrodes were placed on each ankle, and were held in place with 50 millimeter (two inch) wide tape. I was not aware of Schwartz's (1976) work when the EMG electrode placements were selected; suggestions for future studies are discussed in chapters 4 and 5.

An ohmmeter was used to check contact resistance between each pair of electrodes. The input impedance of the data acquisition amplifiers was 10 megohms, and electrode contact resistances of up to 50,000 ohms were allowed. If an electrode pair exceeded this resistance, they were removed and the skin was scrubbed until a low resistance contact could be obtained.

Skin resistance (GSR/BSR) measurements were made with 13 millimeter (half inch) diameter flat silver electrodes attached to the ring and middle fingers of the left hand, with velcro elastic fingerbands. Peripheral skin temperature was measured with a thermistor probe taped to the left index finger tip.

Once all electrodes were properly connected, EEG data were recorded from each channel, for a brief period, on a 100 Hz bandwidth heat-writing chart recorder. Thus the EEG signals were checked for gross artefacts such as scalp muscle twitches or electronic equipment failures. The range and sensitivity settings on the physiological data acquisition instruments were noted and fed to the computer via a keyboard, for storage in memory along with the experimental data.

Each subject was told that a series of cartoon slides would be shown, and that the five pushbuttons on a small box, held in the subject's lap, corresponded to the possible responses (identified by the numbers one through five) to each cartoon. They were asked to "push the button corresponding to the response which most closely matches how you feel at the moment, not necessarily what you would say in the situation depicted." Subjects could take as much time as they wanted to choose a response, but could only push a single button. The computer caused the slide tray to advance to the next slide only after a response button was pushed. The screen was kept blank for a four second interstimulus interval between slides. Subjects were asked to make pushbutton responses with their right hands, to remain relaxed and to move as little as practical while viewing the slides.

The presentation of the slides and the acquisition of the physiological data were controlled by a computer program, SLIDE, which was executed after I had left the subject alone in the living room, and after the subject reported that he or she was comfortable, relaxed and ready to begin. A note was made, during the presentation of the slides, of slides during which the subject coughed or moved unusually. I viewed a video display of physiological data during the experiment, watching for any indications of electrode slippage or equipment failure.

After the 49 slides were shown and the physiological data were recorded in the computer's memory, the data were dumped onto cassette tape, to preserve them for further analysis. I returned to the living room and rechecked the contact resistances of all electrode pairs. In every case these had improved during the session. The electrodes were disconnected, and the subject was asked for his or her subjective impression of the experiment. Each subject was thanked for participating in the experiment, and offered an opportunity to look over the experimental results, once the data analysis was completed.

The computer program SLIDE, which collected and partially analyzed the data, was modified after eight subjects had participated in the study. Additional 16 dimensional EEG data were collected for the last four subjects. These four subjects were among the nine whose temporal EEG was monitored. The collection of further data was precluded by my incarceration.

Chapter 3

RESULTS

An important part of the data reduction for this experiment was done in real-time, while the experiment was running. The balance of the data analysis was done off-line, but on the same 8080A computer system. The results of these analyses are presented, not in the order of calculation, but rather in logical sequence.

Real-Time Data Analysis

The assembly language computer program SLIDE managed real-time data collection and analysis as it supervised the experiment. Data were collected and summarized for storage in the computer's memory. Separate data storage space was allocated in memory for responses to each of the 49 slides.

The slowly changing physiological data, skin temperature, EMG and GSR/BSR, were sampled 12 times each second. The computer retained only a few summary data for each of these measures, for each slide: the initial value (when the slide first flashed on the projection screen), the final value (collected when the subject pushed a button in response to the slide), the total of all samples collected while the slide was viewed and the total number of samples collected for that slide.

In the case of EEG, the computer stored considerably more detailed data. For each of the two EEG channels, each half cycle of the EEG signal was treated as an independent event. Its duration (period) was measured in 1/2000ths of a second, and its peak amplitude was measured in microvolts. Using these two data to describe each half cycle of EEG, the computer was programmed to sort each half cycle into one of 128 categories, and count the total number of events occurring in each category, for each slide and each EEG channel. The result of this sorting and counting process was a two dimensional matrix of numbers, representing a three dimensional amplitude-frequency histogram. A 128 point histogram was produced and stored for each EEG channel and each slide. Thus, for one subject, the computer calculated 98 histograms. Each histogram was stored in memory as a two dimensional matrix organized 8 x 16, with 16 frequency categories and eight amplitude subcategories in each frequency category. The boundaries between the amplitude and frequency categories appear in Table 1.

After data had been collected from the first eight subjects in the experiment, a few preliminary univariate analysis of variance calculations were done for the 128 dimensional EEG data. The results from these (discussed in detail below) were not promising and the SLIDE program was modified to store additional EEG data. For each of the two EEG channels, 16 new data categories were created, corresponding to the 16 frequency categories in Table 1. The total amplitude of all EEG half cycles in each frequency category, during each slide, was calculated and stored. These new EEG data were collected for the last four subjects. This had the advantage over the 128 point histogram data of finer amplitude resolution. The lower dimensionality of these new EEG data also made them much more manageable statistically. Data collection was interrupted due to my incarceration.

Table 1 Frequency and Amplitude Category Boundaries

FREQUENCY (HERTZ)	AMPLITUDE (MICROVOLTS, PEAK)
below 4	0 - 1
4 – 5	1 - 2
5 - 6	2 - 4
6 - 7	4 - 8
7 - 8	8 - 16
8 - 9	16 - 32
9 - 10	32 - 64
10 - 11	64 - up
11 - 12	
12 - 13	
13 - 14	
14 - 16	
16 - 18	
18 - 20	
20 - 22	
22 - up	

Notes. If a datum fell on a category boundary, it was sorted into the lower category.

In addition to period-amplitude analysis of each channel of EEG, the SLIDE program compared the relative timing of the beginnings of half cycles in the two channels so that the phase angle between the two signals could be calculated. The two channels of EEG were not necessarily at the same frequency at all times so the concept of phase angle between them was not always meaningful, nevertheless it was hoped that these data would prove useful in discriminating among egostates.

Phase angle is a relative measure, and was calculated both possible ways: channel R vs.channel L and channel L vs.channel R. The first calculation was done at the end of every channel R half cycle, and the second calculation was done at the end of every channel L half cycle. Represent the period of a channel R half cycle as P(R) and the period of time from the beginning of the last channel L half cycle until the present instant as P(RL), then the phase angles were calculated as:

R vs.L phase = P(RL)/P(R)   L vs.R phase = P(LR)/P(L)

If both of these ratios were zero (i.e., if P(RL) = P(LR) = 0), the two channels would be exactly in phase, an unlikely condition. If one ratio were close to one and the other small, this would indicate a small phase angle or one close to 180 degrees. A 90 or 270 degree phase difference would be expressed as equal ratios of .5, assuming equal frequencies.

The range of each phase angle was divided into eight equal categories, and each phase angle datum was sorted into one of these eight categories and counted as an event. For each slide, there were two phase data vectors, each containing eight categories. Each category covered a 22.5 degree phase angle span.

The results of the on-line data analysis were displayed to me, on the video screen, as the experiment was running. These data were also tape recorded for later, off-line analysis.

Within-subjects Off-line Data Analysis

The initial off-line data analysis was within subjects. Each subject's data were analyzed separately. The main within-subjects analytical effort was focussed on the EEG data.

The slides were viewed for varying periods of time, and thus the data from the 49 slides comprising one subject's record were not directly comparable. The number of events in any EEG category was dependent on both the amount of EEG activity in the category and on the length of time the slide was viewed.

This problem was solved by normalizing the EEG data by dividing each datum by the period of time its slide was viewed.

A computer program was written to normalize the 128 point EEG histogram data, calculate averages for each egostate, overall averages for each category and univariate F statistics for each category. Although a few mildly ($p<.05$) significant F statistics turned up in these calculations, the number of these did not exceed chance expectation. There was insufficient computer memory space available to calculate a multivariate analysis of variance (MANOVA) for all 128 dimensions, but it was clear that the results of such a calculation would not have been significant.

One way of conceptualizing the 128 dimensional EEG histogram data for each subject is as a collection of 49 points in 128 dimensional hyperspace. A computer program was written to calculate the centroids of the five groups of points corresponding to the five egostates, and to calculate the distances between them (by an RMS distance measure). The result of this calculation was that the five groups overlapped, their diameters were much larger than the distances between them, for each subject's data.

The 16 dimensional EEG data for each channel for the last four subjects were then analyzed. The EEG amplitude density in each frequency category was calculated by dividing the total amplitude in each category by the period of time the slide was viewed. It might be worthwhile to point out that this amplitude density datum could be increased either by a few high amplitude events or by a large number of low amplitude events. MANOVA calculations failed to find any significant differences in amplitude density, within subjects, among the egostates.

The non-EEG data were converted from the arbitrary units of measurement created by the VCO-clock system, and were printed out in engineering units (i.e., microvolts for EMG, degrees Celsius for temperature and ohms for BSR). Univariate within subjects statistical analyses of these data were also disappointing, in that no significant differences were found among the egostates. The next approach was to analyze data across subjects.

Across-subjects Off-line Data Analysis

The different subjects who participated in the experiment had varying baseline or resting levels for each physiological measure, and their data could not be directly compared with each other. Each subject's data were Z transformed within each physiological measure and across egostates, to standardize the data and make them comparable across subjects. This procedure produced a single data set with 196 data. Table 2 shows how these data were distributed among the egostates (as defined by subjects' pushbutton responses to the slides).

Table 2 Number of Responses in Each Egostate

	EGOSTATE				
SUBJECT	AC	RC	A	PP	NP
E.S.	5	12	22	5	5
A.L.	8	6	13	12	10
D.W.	7	4	19	9	10
A.R.	7	9	15	10	8
total for all subjects	27	31	69	36	33

The non-EEG data were then subjected to univariate analyses of variance (ANOVA), to look for differences among the egostates in each non-EEG variable. The results of these ANOVA calculations are in Table 3. These calculations were made for the pooled data from all 12 subjects. The data analyzed were: final minus average EMG, average EMG, final minus average BSR, final minus initial BSR, latency (the period of time a slide was viewed was also the time required for a response to be selected), the average GSR and the final minus initial skin temperature data. Table 4 shows the mean Z score values for the significant data.

Table 3 Univariate Analyses of Variance for Non-EEG data

SOURCE	df	MS	F	R
ankle-ankle EMGF-EMGA	4/289	2.00	2.07	2.9%
frontalis EMGF-EMGA	4/238	1.07	1.08	1.8%
all EMGF-EMGA	4/533	1.86	1.90	1.4%
EMGA	4/533	.95	1.12	.8%
BSRF-BSRA	4/582	4.42	4.16*	2.8%
BSRF-BSRI	4/582	3.94	4.21*	3.2%
N (latency)	4/582	3.91	4.05*	2.8%
GSRA	4/582	4.00	5.24**	3.6%
TEMF-TEMI	4/582	1.55	1.59	1.1%

Notes. * p<.005 ** p<.001

Table 4 Mean Z Scores for Significant Non-EEG Data

	EGOSTATE				
SOURCE	AC	RC	A	PP	NP
BSRF-BSRA	-.07	+.01	+.19	+.04	-.30
BSRF-BSRI	-.21	+.13	+.16	-.09	-.24
N (latency)	+.03	+.35	-.16	+.17	+.15
GSRA	+.23	-.22	-.16	+.16	+.20

Although the available computer power was inadequate for multivariate analysis of the 128 dimensional EEG data, it was clear from univariate calculations that such analysis would not be fruitful. The main EEG data analysis was performed using the 16 dimensional data sets from the last four subjects (these were the only available 16 dimensional EEG amplitude density data). There were four 16 dimensional data sets: the 16 point amplitude density spectra from the right and left hemispheres, the 16 point amplitude density ratio of right to left hemisphere and a 16 dimensional data set made up from the two eight dimensional phase data vectors.

The left and right hemisphere EEG amplitude density data and the phase data were analyzed as three separate data sets because they were collected separately and because I hoped that each additional data set would reveal further differences among the egostates.

The right/left ratio data were created from the raw data in an effort to check for differences in EEG amplitude between the two hemispheres, among the egostates. Such differences would not appear in the amplitude density data because of the Z transformation used to create those data sets.

MANOVA techniques were used to analyze each of these 16 dimensional data sets, in an effort to detect differences among the egostates, after the last four subject's data were Z-transformed and pooled, as though they were drawn from a single subject.

Multivariate analysis of variance methods assume equality of group dispersions (which corresponds to the more familiar univariate assumption of equal group variances). The Box test for equality of group dispersions (Cooley & Lohnes, 1971) was applied to all four 16 dimensional EEG data sets, resulting in rejection of this hypothesis in for all but the right hemisphere amplitude density data. These results appear in Table 5.

Cooley and Lohnes (1971) suggest that MANOVA procedures are robust with respect to departures from equality of group dispersion, and that the Box test can sometimes be embarrassingly sensitive. MANOVA calculations were therefore computed by several different methods, in an effort to detect significant differences among the egostates. These yielded varying results, probably due to the inequality of group dispersions.

Two of the MANOVA methods used Wilks' lambda, the ratio of the determinants of E, the error sum of squares and cross products matrix, and T, the total sum of squares and cross products matrix (Morrison, 1976). One such computation yielded a chi-squared variate and the other yielded an F statistic, both of which are approximations. These appear in Table 6, and were calculated from lambda by the equations below.

$\Lambda^2 = -[N - r - 1/2(u - g + 1)] \ln \Lambda$ where $N = 196$, $r = 5$, $u = 16$ and $g = 4$.

$F = y(1 - y)(df2/df1)$ where $y = \Lambda^{1/s}$

$s = [(u*u*g*g - 4)/(u*u + g*g - 5)]$, $df1 = u*g$ and

$df2 = s[(N-1) - (u + g + 1)/2] - (u*g - 2)/2$.

The other two MANOVA computations used the ratio of the between groups sum of squares and cross products matrix and the error (within groups) sum of squares and cross products matrix (HE^{-1}). One approach, from Roy (in Morrison, 1976) was to find c, the greatest root of this matrix, and compare the quantity theta = c/(1 + c) to the values in Heck's charts of the upper percentage points of the largest characteristic root. The other method used the Lawley-Hotelling trace statistic, where a chi-squared variate was computed from the product of the trace of the HE^{-1} matrix and N, the number of data points (Morrison, 1976). These results appear in Table 7.

Table 5 Box Tests of the Equality of Group Dispersions for the 16 Dimensional EEG Amplitude Density and Phase Data

		DISPERSIONS FOR EACH EGOSTATE (x10)				
SOURCE	F	AC	RC	A	PP	NP
left hemisphere	1.30*	1	6	5430	16	24
right hemisphere	1.19	6	247	17383	140	78
phase angle data	1.37*	.02	18	205	3	.1
right/left ratio	1.32*	3	874	16016	34	6573

Notes. df= 544/13544 * $p<.001$

Table 6 MANOVA Tests of the Equality of Group Means, using Lambda, for the 16 Dimensional EEG Amplitude Density and Phase Data

SOURCE	LAMDA	CHI-SQUARED	F
left hemisphere	.668	74.5	1.17
right hemisphere	.6749	72.3	1.14
phase angle data	.7243	59.5	.93
right/left ratio	.7158	61.7	.96

Notes. df = 64 for chi-squared, 64/691 for F

Table 7 MANOVA Tests of the Equality of Group Means, using HE $^{-1}$ for the 16 Dimensional EEG Amplitude Density and Phase Data

SOURCE	THETA	TRACE	CHI-SQUARED
left hemisphere	.179*	.4328	84.8**
right hemisphere	.153	.4199	82.3*
phase angle data	.156	.3433	67.3
right/left ratio	.132	.3507	68.7

Notes. df = 64 for chi-squared; s = 4, m = 5.5, n = 87 for theta

* $p<.05$ ** $p<.025$

Univariate ANOVA calculations were also computed for each of the 16 dimensional data sets. The results of these calculations, together with mean Z scores for each datum, are presented in Tables 8 through 10.

Table 8 EEG Amplitude Density ANOVA Results and Mean Z Scores

FREQUENCY (Hertz)	MS	F	R	MEAN Z SCORES BY EGOSTATE AC	RC	A	PP	NP
LEFT HEMISPHERE								
below 4	3.08	3.27**	6.4%	+.29	-.26	-.23	+.19	+.30
4 - 5	4.29	4.69****	8.9%	-.25	-.05	-.19	+.02	+.62
5 - 6	.39	.39	.8%	+.09	-.01	+.08	-.15	-.06
6 - 7	.68	.68	1.4%	-.12	+.09	+.13	-.12	-.12
7 - 8	1.06	1.08	2.2%	+.05	+.14	+.11	-.19	-.20
8 - 9	.96	.97	2.0%	+.04	-.20	+.13	+.06	-.20
9 - 10	.39	.38	.8%	+.16	-.00	+.04	-.14	-.05
10 - 11	1.84	1.90	3.8%	-.12	+.22	+.13	-.03	-.36
11 - 12	.81	.82	1.7%	-.11	+.03	+.14	-.21	-.00
12 - 13	.88	.89	1.8%	+.09	-.04	+.14	-.20	-.11
13 - 14	2.74	2.89**	5.7%	-.07	+.35	+.13	-.12	-.40
14 - 16	3.44	3.68***	7.2%	+.32	+.14	+.16	-.41	-.29
16 - 18	1.70	1.75	3.5%	+.12	+.21	+.10	-.30	-.18
18 - 20	2.79	2.95**	5.8%	+.05	+.33	+.13	-.34	-.27
20 - 22	2.91	3.08**	6.1%	+.08	+.33	+.13	-.32	-.31
22 - up	3.18	3.35**	6.6%	+.14	+.15	+.21	-.41	-.26
RIGHT HEMISPHERE								
below 4	2.53	2.66*	5.3%	+.33	-.24	-.18	+.04	+.30
4 - 5	1.80	1.86	3.8%	+.20	-.20	-.18	+.24	+.14
5 - 6	1.44	1.47	3.0%	+.08	+.06	-.18	-.04	+.30
6 - 7	2.29	2.39	4.8%	+.27	-.29	-.07	+.31	-.14
7 - 8	.36	.36	.8%	-.02	+.10	-.06	-.08	+.14
8 - 9	1.96	2.03	4.1%	-.10	+.42	-.08	-.21	+.07
9 - 10	.88	.89	1.8%	+.12	-.23	+.10	-.14	+.05
10 - 11	.49	.50	1.0%	+.17	-.02	+.05	-.08	-.15
11 - 12	1.71	1.76	3.6%	-.30	+.33	-.06	+.13	-.07
12 - 13	.93	.94	1.9%	-.22	+.23	+.06	-.05	-.12
13 - 14	1.34	1.37	2.8%	-.19	+.11	+.11	+.10	-.29
14 - 16	1.74	1.80	3.6%	-.13	+.26	+.14	-.15	-.26
16 - 18	3.23	3.44**	6.7%	-.19	+.22	+.26	-.31	-.26
18 - 20	1.78	1.84	3.7%	-.14	+.13	+.20	-.28	-.12
20 - 22	2.53	2.65*	5.3%	-.16	+.21	+.16	+.02	-.43
22 - up	1.79	1.85	3.7%	-.16	+.21	+.14	-.03	-.33

Notes. df = 4/191 * p<.05 ** p<.025 *** p<.01 **** p<.005

Table 9 EEG Phase Angle ANOVA Results and Mean Z Scores - Right vs. Left Hemisphere

PHASE ANGLE (degrees)	MS	F	R	MEAN Z SCORES BY EGOSTATE AC	RC	A	PP	NP
0-22.5	1.22	1.25	2.5%	-.18	-.02	-.11	+.29	+.08
22.5-45	.78	.79	1.6%	-.24	+.10	+.11	-.04	-.09
45-67.5	1.67	1.72	3.5%	-.05	+.30	+.10	-.25	-.18
67.5-90	2.35	2.46*	4.9%	-.14	+.05	+.27	-.19	-.28
90-112.5	1.54	1.59	3.2%	+.07	+.34	+.01	-.18	-.20
112.5-135	3.38	3.62**	7.0%	-.03	+.34	+.17	-.18	-.46
135-157.5	1.11	1.13	2.3%	-.02	+.17	+.12	-.19	-.19
157.5-180	1.98	2.06	4.1%	-.02	+.18	+.18	-.23	-.29

Notes. df = 4/191 * p<.05 ** p<.01

Table 10 Right/Left EEG Amplitude Ratio ANOVA Results and Mean Z Scores

FREQUENCY (Hertz)	MS	F	R	MEAN Z SCORES BY EGOSTATE AC	RC	A	PP	NP
below 4	.49	.49	1.0%	+.23	-.03	-.02	-.11	-.00
4 - 5	1.18	1.20	2.5%	+.29	-.10	-.08	+.16	-.15
5 - 6	1.21	1.23	2.5%	-.05	+.01	-.14	-.01	+.32
6 - 7	.74	.75	1.5%	+.12	-.20	-.04	+.18	-.02
7 - 8	.83	.84	1.7%	-.07	-.05	-.08	-.01	+.28
8 - 9	1.56	1.61	3.3%	-.13	+.34	-.12	-.11	+.15
9 - 10	.85	.76	1.6%	-.01	-.27	+.09	+.07	+.12
10 - 11	.68	.69	1.4%	+.18	-.13	-.02	-.12	+.16
11 - 12	1.48	1.52	3.1%	-.04	+.31	-.17	+.15	-.05
12 - 13	.74	.74	1.5%	-.20	+.06	-.08	+.11	+.16
13 - 14	1.02	1.04	2.1%	+.06	-.25	-.06	+.12	+.19
14 - 16	1.03	1.05	2.1%	-.29	-.03	-.03	+.19	+.11
16 - 18	1.31	1.34	2.7%	-.31	-.11	+.02	+.04	+.26
18 - 20	1.83	1.90	3.8%	-.28	-.26	+.03	+.11	+.28
20 - 22	.29	.29	.6%	-.07	-.03	-.05	+.15	+.02
22 - up	2.36	2.48*	4.9%	-.25	-.05	-.15	+.40	+.12

Notes. df = 4/191 * p<.05

A discrepancy between the L vs.R and R vs.L phase data led to a careful investigation of the raw data and the SLIDE program which collected the data. A program error in SLIDE was found which spoiled the collection of the Left vs.Right phase data and these data were discarded. The discovery of this error led to a further careful check of the other raw data, and two more minor errors in the Z transforming programs were found and corrected. An eight dimensional MANOVA of the R vs.L phase data yielded no significance.

The significant findings in the 16 dimensional EEG amplitude density data led to a further investigation of the EEG data. The 128 point EEG data were analyzed as eight 16 dimensional subsets, using MANOVA, across the last four subjects, with non-significant results. New 16 dimensional data sets were then created by totaling the number of half-cycles of EEG within each of the frequency categories. When divided by the length of time each slide was viewed, these calculations yielded a frequency of occurrence datum for each frequency category. The average amplitude of the EEG half-cycles in each frequency category was calculated by dividing the amplitude density datum by the frequency of occurrence datum, yielding yet another 16 dimensional data set for each hemisphere of the brain.

MANOVA calculations for these four 16 dimensional data sets yielded results not quite reaching significance, which are presented in Table 11. The frequency of occurrence data are labeled "Fr" and the amplitude data are labeled "A." Although the differences between the egostates in the left hemisphere Fr and A data sets did not quite reach significance, when considered as 16 dimensional sets, the ANOVA calculations associated with these are presented in Table 13, for the light they may shed on the EEG amplitude density data in Table 8 (they show that the high amplitude density associated with the Parent egostates in the low frequency bands is not due to a few high amplitude events). Univariate ANOVA calculations for left hemisphere average amplitude, frequency of occurrence and amplitude density data, summed across all frequency categories, appear in Table 12. These results show significant differences among the egostates in each case.

Table 11 16 Dimensional MANOVA Results for EEG Average Amplitude and Frequency of Occurrence Data

SOURCE	F	LAMBDA	THETA	TRACE

left hemisphere Fr	1.14	.676	.172	.419
left hemisphere A	.95	.718	.125	.347
right hemisphere Fr	1.06	.694	.160	.391
right hemisphere A	.84	.747	.113	.306

Notes. df = 64/691 for F; s = 4, m = 5.5, n = 87 for theta

Table 12 ANOVA Results and Mean Total Z Scores for all Categories of EEG Left Hemisphere Data

				MEAN Z SCORES BY EGOSTATE				
SOURCE	MS	F	R	AC	RC	A	PP	NP
Fr	3.21	3.92**	7.6%	+.02	+.35	+.45	-.54	-.86
A	17.09	2.65*	5.3%	+.35	+.59	+.32	-1.09	-.48
A density	35.96	4.19**	8.1%	+.36	+.68	+.65	-1.36	-.97

Notes. df = 4/191 * p<.05 ** p<.005

Table 13 ANOVA Results and Mean Z Scores for Left Hemisphere EEG Average Amplitude and Frequency of Occurrence Data

FREQUENCY (Hertz)	MS	F	R	MEAN Z SCORES BY EGOSTATE AC	RC	A	PP	NP
Amplitude Average								
below 4	.30	.30	.6%	+.13	+.05	+.02	-.09	-.10
4 - 5	.75	.75	1.6%	+.08	+.06	+.08	-.25	-.00
5 - 6	1.71	1.76	3.6%	+.10	+.23	+.06	-.36	-.01
6 - 7	1.16	1.18	2.4%	+.13	+.17	+.05	-.29	-.06
7 - 8	2.68	2.83*	5.6%	-.07	+.05	+.22	-.45	+.05
8 - 9	.14	.14	.3%	+.04	-.07	+.04	-.08	+.03
9 - 10	.42	.42	.9%	-.17	+.00	+.10	-.02	-.06
10 - 11	1.18	1.20	2.4%	+.07	+.32	-.06	-.17	-.04
11 - 12	1.24	1.26	2.6%	+.14	+.20	+.01	-.30	-.00
12 - 13	1.89	1.96	3.9%	+.12	+.19	+.10	-.38	-.07
13 - 14	2.31	2.41	4.8%	+.18	+.21	+.12	-.33	-.24
14 - 16	2.22	2.31	4.6%	+.29	+.01	+.15	-.29	-.25
16 - 18	1.37	1.40	2.9%	+.08	+.11	+.14	-.27	-.17
18 - 20	2.25	2.35	4.7%	-.00	+.32	+.12	-.30	-.22
20 - 22	4.09	4.44***	8.5%	+.23	+.38	+.11	-.40	-.34
22 - up	2.00	2.07	4.2%	+.15	+.19	+.13	-.28	-.26
Frequency of Occurrence								
below 4	3.39	3.63**	7.1%	+.16	-.24	-.26	+.24	+.37
4 - 5	4.51	4.95***	9.4%	-.32	-.13	-.20	+.23	+.55
5 - 6	.29	.29	.6%	-.01	-.15	+.08	+.02	-.03
6 - 7	.83	.84	1.7%	-.25	-.04	+.12	+.09	-.11
7 - 8	.63	.63	1.3%	+.12	+.11	+.01	-.00	-.23
8 - 9	.76	.77	1.6%	-.01	-.16	+.08	+.15	-.17
9 - 10	.51	.51	1.1%	+.20	+.01	-.01	-.16	+.02
10 - 11	1.20	1.22	2.5%	-.06	+.11	+.12	+.01	-.32
11 - 12	.73	.74	1.5%	-.09	-.11	+.16	-.13	-.01
12 - 13	.39	.39	.8%	-.01	-.07	+.09	+.04	-.15
13 - 14	2.42	2.54*	5.0%	-.21	+.30	+.11	+.03	-.38
14 - 16	2.40	2.51*	5.0%	+.22	+.21	+.11	-.34	-.24
16 - 18	1.79	1.85	3.7%	+.16	+.25	+.07	-.27	-.22
18 - 20	2.55	2.68*	5.3%	+.12	+.30	+.11	-.33	-.25
20 - 22	1.33	1.36	2.8%	-.05	+.20	+.13	-.18	-.22
22 - up	3.44	3.69**	7.2%	+.11	+.13	+.24	-.44	-.25

Notes. df = 4/191 * p<.05 ** p<.01 *** p<.005

The results presented up to this point clearly indicate that there are measurable physiological differences among the five egostates which were defined by subjects' responses to the slides. It is possible that significant differences among the egostates would have been found in all physiological measures if data had been collected from more subjects. However, with data from four subjects, the only significant differences were found in the left hemisphere EEG amplitude density data and four of the non-EEG measures. These results justified further analysis in an effort to learn if these differences were sufficient to be usable in identifying egostates from physiological data alone.

Discriminant Analysis and Classification

Once the foregoing analyses were completed, the next steps were: (1) to select the most useful set of variables for classification of the responses into egostates from physiological data and (2) to determine how well the classifications actually fit the egostates defined by the subjects' pushbutton responses. Stepwise discriminant analysis was chosen as a selection technique. This mathematical approach tests a set of variables to find the one with the most discriminating power and enters it into the group of selected variables if its discriminating power meets a preselected minimum standard. Then the group of selected variables is scanned to see how much decrease in discriminating power would result from removing each variable, and this is compared to a preselected tolerance level. If a variable falls below the tolerance, it is removed. The process continues in steps like these until no new variable can be entered or removed.

Of the various 16 dimensional data sets examined, only one showed significance in a MANOVA test, the left hemisphere amplitude density data. The remaining 16 dimensional data sets were not used in further analysis. The four significant non-EEG variables (BSRF-BSRI, BSRF-BSRA, N[latency], and GSRA) were combined with the left hemisphere amplitude density data to form a 20 dimensional data set for the first stepwise discriminant analysis (the computer had sufficient memory for a maximum of 20 dimensions).

For this analysis, the threshold values of F statistics for entry or removal of a variable were set at .8. The result was that 11 variables were entered into the data set, nine were not. The order in which variables were entered and their F to remove values are reported in Table 14, together with F to enter values for the variables not included. The discriminant F statistic is also reported for each step of the analysis, with its degrees of freedom.

Table 14 20 Dimensional Stepwise Discriminant Analysis of Left Hemisphere Amplitude Density Data and Non-EEG Data

VARIABLE	F TO ENTER	F TO REMOVE	DISCRIMINANT F	df
4 - 5 Hz		4.69	4.69	4/191
22 - up Hz		3.26	3.96	8/380
N(latency)		2.23	3.37	12/500
BSRF-BSRA		2.31	3.12	16/575
below 4 Hz		1.84	2.87	20/621
13 - 14 Hz		1.32	2.61	24/650
14 - 16 Hz		1.27	2.41	28/669
22 - up Hz	.72		2.71	24/650
11 - 12 Hz		1.18	2.49	28/669
GSRA		1.21	2.33	32/680
8 - 9 Hz		.98	2.18	36/688
7 - 8 Hz		.91	2.05	40/692
9 - 10 Hz		.81	1.93	44/694
6 - 7 Hz	.79			
10 - 11 Hz	.71			
20 - 22 Hz	.58			
5 - 6 Hz	.58			
22 - up Hz	.57			
18 - 20 Hz	.53			
BSRF-BSRI	.42			
6 - 7 Hz	.39			
16 - 18 Hz	.07			

The six variables not entered in the group of selected variables, but with highest F to enter values, were combined with the selected variables in Table 14 and the three variables in Table 12: the left hemisphere average frequency datum (Fr), the left hemisphere average amplitude datum (A) and the left hemisphere overall amplitude density (A density), thus forming a new 20 variable data set. A new stepwise discriminant analysis was then performed, with F to enter and remove threshold values set at .5. The results of this analysis are displayed in Table 15, in the same format used in Table 14.

Table 15 20 Dimensional Stepwise Discriminant Analysis of Non-EEG Data and Selected Left Hemisphere EEG Data

VARIABLE	F TO ENTER	F TO REMOVE	DISCRIMINANT F	df
4 - 5 Hz		4.69	4.69	4/191
A density		4.28	4.47	8/380
BSRF-BSRA		2.26	3.73	12/500
N(latency)		2.66	3.47	16/575
13 - 14 Hz		1.79	3.14	20/621
GSRA		1.40	2.85	24/650
11 - 12 Hz		1.27	2.62	28/669
8 - 9 Hz		1.02	2.42	32/680
10 - 11 Hz		1.03	2.27	36/688
18 - 20 Hz		.73	2.11	40/692
below 4 Hz		.60	1.97	44/694
14 - 16 Hz		.75	1.86	48/695
A		.79	1.78	52/695
18 - 20 Hz	.43		1.89	48/695
Fr		.59	1.79	52/695
12 - 13 Hz		.65	1.71	56/695
A density	.49		1.80	52/695
9 - 10 Hz		.51	1.71	56/695
5 - 6 Hz		.55	1.63	60/693
22 - up Hz	.49			
7 - 8 Hz	.41			
A density	.39			
18 - 20 Hz	.14			
20 - 22 Hz	.07			

The result of this discriminant analysis was that a set of 15 variables was selected as being those most useful for distinguishing among the five egostates. To check the usefulness of this set of variables, group classification functions were then calculated, using this set of variables, by Jennrich's method (1977), which is another form of discriminant analysis. A group classification function is a linear combination of the variables together with a classification function constant. The five sets of coefficients and their related classification constants are presented in Table 16.

Table 16 Group Classification Coefficients and Constants and Final Discriminant F to Remove Values

VARIABLE	FINAL F TO REMOVE	COEFFICIENTS AND CONSTANTS BY EGOSTATE AC	RC	A	PP	NP
4 - 5 Hz	3.23	-.305	-.246	-.048	-.083	+.675
BSRF-BSRA	2.85	-.106	-.439	+.415	-.091	-.316
N(latency)	2.79	+.168	+.331	-.331	+.293	+.018
below 4 Hz	1.61	+.792	-.343	-.111	-.118	-.110
11 - 12 Hz	1.43	-.315	-.232	+.104	-.038	+.405
14 - 16 Hz	1.39	+.728	-.241	-.013	-.176	+.039
13 - 14 Hz	1.14	-.115	+.211	-.050	+.400	-.283
A	1.11	-.089	+.168	+.035	-.169	-.074
Fr	1.08	+.266	+.049	+.041	-.289	-.288
8 - 9 Hz	1.04	-.001	-.323	+.151	+.160	-.101
12 - 13 Hz	.81	+.022	-.347	+.094	-.003	+.221
GSRA	.80	+.112	-.240	+.080	+.192	-.250
9 - 10 Hz	.59	+.312	-.086	-.030	-.095	+.072
10 - 11 Hz	.58	-.162	+.135	+.032	+.191	-.178
5 - 6 HZ	.55	+.189	-.139	+.084	-.171	+.009
CONSTANT		-.347	-.276	-.160	-.247	-.464

The group classification coefficients [B(I,G) for the Ith variable and the Gth egostate] and constants [A(G) for the Gth egostate] were used to calculate the probability P(G) that a slide, J, belonged to egostate G, by the method set out below.

$P(G) = \exp[D(G)]/Q$ where $Q = \exp[D(1)] + ... + \exp[D(5)]$,

$D(E) = A(E) + X(J,1)*B(1,E) + ... + X(J,15)*B(15,E)$,

and X(J,K) is the datum for the Kth physiological measure and the Jth slide.

The result of these classification calculations was a set of five P(G) values for each of the 196 slides, corresponding to the posterior probability that each slide was classified into egostate G from the physiological data. If each slide is classified into the egostate for which it has the highest posterior probability, the confusion matrix in Table 17 results. The percentage figures in parenthesis are the percentage of responses correctly classified.

Table 17 Confusion Matrix for Classification of Slides into Egostates from Selected Physiological Data

RESPONSE EGOSTATE	NUMBER OF EVENTS CLASSIFIED BY EGOSTATE				
	AC	RC	A	PP	NP
AC	10 (37%)	6	4	5	2
RC	3	15 (48%)	3	7	3
A	13	9	27 (40%)	8	12
PP	3	4	3	17 (47%)	9
NP	4	2	5	4	18 (55%)

Note. The RESPONSE EGOSTATE is the egostate corresponding to the response chosen by the subject.

Table 17 shows the number and percentage of "direct hits" and misses in classification. The overall percentage of hits was 44.4%. An additional 24% of the slides were "near misses," defined as slides for which the response egostate posterior probablity was second highest and exceeded 20%. These near misses were data points which fell near the classification boundaries.

The possibility existed that substantial variations among subjects might be detected. To check for this, Table 18 shows the distributions of classified egostates vs. response egostates for each subject.

Table 18 Classified vs. Response Egostates for Each Subject

RESPONSE EGOSTATE	NUMBER OF EVENTS CLASSIFIED BY EGOSTATE AC	RC	A	PP	NP
SUBJECT E.S.					
AC	3 (60%)	1	0	1	0
RC	1	4 (33%)	2	4	1
A	6	2	7 (32%)	2	5
PP	0	0	0	4 (80%)	1
NP	2	1	0	1	1 (20%)
total	12	8	9	12	8
SUBJECT A.L.					
AC	3 (38%)	2	2	0	1
RC	0	4 (67%)	0	2	0
A	2	2	6 (46%)	1	2
PP	1	2	1	6 (50%)	2
NP	1	1	1	1	6 (60%)
total	7	11	10	10	11
SUBJECT D.W.					
AC	1 (14%)	3	1	2	0
RC	0	2 (50%)	1	1	0
A	4	3	7 (37%)	2	3
PP	0	1	2	4 (44%)	2
NP	1	0	4	1	4 (40%)
total	6	9	15	10	9
SUBJECT A.R.					
AC	3 (43%)	0	1	2	1
RC	2	4 (44%)	0	1	2
A	1	2	7 (47%)	3	2
PP	2	1	0	3 (30%)	4
NP	0	0	0	1	7 (89%)
total	8	7	8	10	16
grand total	33	35	42	42	44

To show how the group centroids were separated from each other in this discriminant space, the posterior probabilities for each group mean vector were calculated, as though it were a data point. These are presented in Table 19. It is clear from these results that the group centroids are well separated in this discriminant space.

Table 19 Posterior Probabilities for Group Centroids

RESPONSE EGOSTATE	POSTERIOR PROBABILITY BY EGOSTATE				
	AC	RC	A	PP	NP
AC	34.6%	16.6%	19.6%	16.9%	12.3%
RC	15.8%	32.8%	18.7%	19.4%	13.2%
A	18.5%	18.6%	32.6%	17.4%	12.8%
PP	15.4%	18.7%	16.9%	31.6%	17.3%
NP	13.2%	14.9%	14.6%	20.3%	37.0%

The net result of analysis of the data from the last four subjects in this study indicates not only that physiological correlates of egostates exist, but also that recognition of egostates is possible, from physiological data, by use of discriminant classificaion equations.

Chapter 4

DISCUSSION

The final results of efforts to classify the 196 slides into egostates from physiological data, presented in Table 17, support the hypothesis that identity states can be recognized from pattern analysis of physiological data. These results, together with the results presented in earlier tables, also permit some discussion of the physiological correlates of egostates.

The non-EEG data in Table 4 present a consistent picture. Recalling that Jung (1918) found long response latencies associated with emotionally evocative stimuli, and that elevated GSRA levels and depressed BSRF-BSRA levels are usually associated with arousal, it appears that the Adult egostate is the least aroused. This is, of course, consistent with TA theory (Berne, 1961). Interestingly, it is the Nurturing Parent egostate which shows the strongest indications of arousal in all of the non-EEG measures.

The EMG data proved not to be very useful because different EMG electrode placements were used for some subjects, and because the EMG electrode placements were chosen without awareness of Schwartz's (1976) work with facial EMG patterns and emotions. In further research along these lines, EMG electrode placements on the corrugator and depressor muscles might yield interesting results.

The skin resistance data proved quite useful. Tables 14 through 16 show that the BSRF-BSRA and GSRA measures both provided useful discriminating information, while BSRF-BSRI was redundant (it correlated highly, .66, with GSRA).

The lack of useful skin temperature responses could easily be due to the long latency usually associated with this response. Useful temperature responses might be collected in a more slowly paced study.

The brainwave data were the main focus of interest. The 128 dimensional EEG data proved to be much less useful than was originally hoped. They were too unwieldy to manipulate statistically, and the low amplitude resolution of the amplitude subcategories proved fatal to any hopes for statistical significance. Some useful information was salvaged from the 128 point data: the number of half-cycles of EEG in each frequency category, a datum which should be stored in future studies of this type.

Only one of the 16 dimensional EEG data sets met the equality of group dispersions assumption of the multivariate linear model. In every other case, the Adult ego state dispersion (see Table 5) was significantly higher than that of the other egostates. This may be interpreted as a possible indication that subjects gave Adult responses in spite of non-Adult feelings. The stimuli in McCarley's cartoons are Adult in nature, and tend to encourage this type of response, in spite of the instructions given to subjects "to pick the response closest to how you feel and not what you might say."

Subjects were asked for their impressions of the experiment after data collection was completed. Most subjects said that they often found that none of the five possible responses really felt correct and that they had been forced to pick a response different from their true feelings. This may be a partial explanation of the 44.4% direct hit level, as well as the high Adult dispersions. It is interesting to note in Table 18 that substantially fewer slides were classified into the Adult egostate by physiological data than by subject response (42 vs. 69), while every other egostate gained members from classification compared to responses (compare the totals in Tables 2 and 18).

In Table 18 the percentage of hits noted in parenthesis is the percentage of responses correctly classified. If we calculate the percentage of classifications which are correct responses instead, we find 64.3% of the Adult classifications to be correct. In other words, though the computer picked fewer slides as members of the Adult group, it was more often correct in these choices than in the average classification (44.4% accuracy). This lends further support for the notion that subjects sometimes picked Adult responses in spite of non-Adult feelings.

The estimation of the percentage of errors likely in classifying a new set of experimental data is not a simple task. Using one set of data to create discriminant coefficients and then using the same set of data to test the reliability of those discriminant coordinates usually leads to an optimistic estimate of accuracy. However, as the number of data points becomes large compared to the number of variables, this error decreases (Lachenbruch & Mickey, 1968), and with 15 variables and 196 data points, the error may be acceptable. Of course, repeating the same procedure with a new, larger sample of subjects would be the ultimate test of across-subject validity.

Some of the errors in classification may have been due to ambiguity in the responses offered with the cartoons. I asked five counselors trained in TA techniques to classify the responses into egostates, and in 6%, 2%, 19%, 26% and 8% of the responses, they disagreed with McCarley.

An additional factor to consider is McCarley's (1974) report of test-retest correlation coefficients ranging from .47 to .73. This low reliability for McCarley's test makes the 44.4% direct hit rate look better than a higher reliability would have. But, of course, it may simply indicate that the same cartoon does not always evoke the same egostate in a person.

The left hemisphere amplitude density data were the only 16 dimensional data set attaining significance on MANOVA. Of course, with more subjects, it is possible (even likely) that other data would have yielded significance. But the superiority of left hemisphere EEG in this discrimination task still needs explanation. The left hemisphere normally manages verbal tasks (Penfield & Roberts, 1974), and the critical parts of the slide were textual, verbal material. The task of reading the stimulus text and the response texts, to select a response, may have been primarily a left hemisphere task. Subjects were asked to use their right hands to push response buttons, and this left hemisphere motor task may have contributed to hemispheric specialization of the EEG response.

Even the significance of the left hemisphere EEG data is marginal (p .05), with data from only four subjects. The four different MANOVA approaches used yielded conflicting results, probably because of the lack of equality of group dispersions. Nevertheless, it seemed justifiable to proceed with further analysis of the left hemisphere EEG data.

The phase data might have reached significance, but for the program error which spoiled collection of Left vs.Right phase data (see Table 9). It would be worthwhile to collect such phase data in any future study of this type.

The most outstanding feature of the left hemisphere amplitude density data in Table 8 is the abundance of low frequency EEG and lack of high frequency EEG associated with the Parent egostates. One possible, though unwelcome, explanation for this might be a high level of movement artefact associated with the Parent states, producing false high amplitude low frequency non-EEG signals. Such movement artefacts would probably be accompanied by high EMG levels in the EEG data, an increase in the amplitude of the 22 - up Hz frequency band.

Amplitude density data do not directly yield information about the amplitude of EEG signals. A high amplitude density could be produced by sustained moderate amplitudes or by occasional high amplitudes. To investigate this question, the data in Tables 11 through 13 were computed from the combination of the 16 dimensional total amplitude raw data and the frequency of occurrence data constructed from the 128 point histograms.

From Table 13 it appears that the high amplitude density in the low frequency bands associated with the Parent egostates is not due to high amplitude movement artefact. The average amplitude in these frequency bands is actually depressed, and the high amplitude density results from a high frequency of occurrence of these low frequency EEG components. The amplitude of the 22 - up Hz frequency band is also depressed, an indication that high amplitude EMG activity probably was not a major factor.

In Table 12 it can be seen that the overall amplitude density for the Parent egostates is substantially lower than the other egostates, probably an indication of general EEG activation. One possible explanation which cannot be eliminated, however, is that slow eye movements may have been more frequent for the Parent egostates, and that the weak low frequency signals from these eye movements might have contaminated the EEG data. Recordings of eye movements should be part of future studies of this kind.

In Table 16 the 15 variables included in the final classification are listed in order of their discriminating power. The most strongly discriminating variable is the 4 - 5 Hz left hemisphere EEG amplitude density measure. From the classification coefficients it can be seen that a peak at this point in the spectrum was a strongly distinguishing feature of the Nurturing Parent egostate.

The Adult egostate's most distinguishing characteristic seems to be elevated BSRF-BSRA, with depressed latency following a close second. A strong peak in the "below 4 Hz" band seems typical of the Adaptive Child egostate, together with a peak in the 14 - 16 Hz band.

There does not seem to be a single variable in Table 16 which peaks strongly for Rebellious Child or Punative Parent. Looking at Table 12, it appears that one difference between these egostates is that the overall frequency of occurrence, average amplitude and amplitude density are substantially lower for the Punative Parent egostate.

From Walter's (1963) reports of theta bursts associated with frustration in children, it might be expected that a peak in the theta frequency range (4 - 8 Hz) would have been associated with the Child egostates. This pattern was not clearly observed. Interestingly, there does seem to be a peak in the 10 - 12 Hz region in the Table 13 average amplitude data for the Rebellious Child egostate, with a weaker peak at the 5 - 6 Hz subharmonic frequency. The Adaptive Child data in the same table show a broad peak in the upper alpha and lower beta bands, from 11 to 16 Hz. Because these results did not reach a high level of statistical significance, they should be considered to be only interesting speculation at this stage.

Returning to Table 16, it is interesting to note that neighboring frequency bands may have widely differing discriminant coefficients, e.g. the 13 - 14 Hz band and the 14 - 16 Hz band. One interpretation of this may be that the frequency bands were too broad, and that future analyses should sort brainwaves into more frequency categories.

It also seems clear that low frequency EEG signals often blocked the measurement of higher frequency EEG signals, due to the capture effect discussed in chapter 1, which is typical of the zero crossing detection technique. This probably accounts in part for the high negative correlation between the upper and lower frequency bands. A possible solution to this difficulty will be discussed in the next chapter.

The most useful result of this study was the confirmation of the usefulness of the amplitude-period-discriminant analysis method of EEG pattern recognition. Further experimental work with more subjects will be needed before definite conclusions can justifiably be drawn regarding specific patterns associated with particular egostates.

Chapter 5

CONCLUSIONS AND IMPLICATIONS

The original motivation for this research was a dissatisfaction with the limitations of existing biofeedback systems. I hoped that patterns of physiological events could be detected which identify interesting events in consciousness, and that a method for the recognition of these patterns could be developed, ideally a method which could be applied in real time physiological data analysis, so that biofeedback training could be conducted for these patterns.

My incarceration cut short the experimental portion of the research, and usable data were collected from only four subjects. Yet the analysis of these data did yield significant differences, in both EEG and non-EEG measures, for the five egostates in the Ego State Inventory, and useful conclusions can be drawn from these data.

It is possible to detect useful physiological correlates of McCarley's (1974) egostates. The primary goal of this research was methodological, but some information about the correlates of egostates was also obtained as a result of the analysis. The Adult egostate was confirmed as the state with the least arousal and shortest response latency, while the Parent egostates were found to exhibit the strongest arousal in all physiological measures.

Of the non-EEG measures, skin resistance (both BSR and GSR) and response latency proved to be useful measures. The EMG electrode placements were chosen poorly and no conclusions could be drawn regarding EMG. The skin temperature data did not show significant results, probably due to the long latency of this response and the fast pace of the experiment (the average slide was viewed for only 20 seconds).

Of the EEG measures, only the left temporal EEG revealed significant differences among the five egostates, though the other EEG measures might have attained significance if more subjects had participated in the experiment. Amplitude-period EEG analysis was demonstrated to be a useful analytical method for this application. The 128 point histogram approach did not prove to be helpful, and the most useful data were the amplitude density, frequency of occurrence and average amplitude measures. A programming error spoiled phase data collection, and no conclusions could be drawn regarding the usefulness of that measure.

Discriminant analysis proved to be a useful analytical method for finding the best subset of variables, and for classification of the slides into egostates. By combining many physiological variables in the final discriminant equation, a classification method results which can obtain respectable accuracy despite variations from subject to subject in physiological response pattern. This may make it possible to avoid the necessity Pinneo and Hall (1975) reported, for example, of computing different recognition templates for every subject.

The Ego State Inventory has a number of flaws when applied in this type of experiment. It is a forced multiple choice test, and subjects frequently found that none of the available responses really applied. The responses were sometimes ambiguous, and even trained TA therapists did not always agree (see chapter 4) on the egostate corresponding to each response. Despite these limitations, the results indicate that the Ego State Inventory can be used as a simple source of stimuli for this sort of research.

Implications for Further Research

A number of ideas for improving data collection and analytical techniques have resulted from this study. The amplitude-period EEG analysis method, with its flexibility, may see more use if some of its limitations can be overcome. The capture effect is probably its most severe limitation, because it allows strong signals to block the measurement of weaker signals of interest.

In speech recognition research, a simple method has been developed for overcoming this limitation, and this method may be profitably applied to EEG analysis in future research. The raw data can be separated into several frequency bands with analog filters, and each band can be independently analyzed by the amplitude-period method. For EEG analysis, as few as three bands would produce a great improvement in analytical scope, by separating the higher amplitude low frequency signals, the medium amplitude alpha-theta signals and the weak high frequency components. If the passbands of the filters in such a system were allowed to overlap slightly, the data from the three detectors could be combined to provide accurate amplitude, amplitude density and frequency of occurrence data for a broad spectrum of EEG signals.

EEG data might be sorted into categories 1/2 Hz or less wide, with the total amplitude and the number of half-cycles in each category being the primary data stored in memory. These data, together with the duration of each epoch, would be sufficient for the calculation of amplitude density, average amplitude and frequency of occurrence spectra.

A biofeedback system for emotion training might include two or more EEG channels, two or more EMG channels (the corrugator and depressor facial muscles are good candidates), eye movement recording and a skin resistance channel. The system would collect d while being trained in the recognition of an event in consciousness. Then stepwise discriminant analysis could be done, to select the best set of variables for classification, and classification coefficients and constants could be computed. In the biofeedback mode, real time data would be used in the calculation of posterior probabilities, using the classification coefficients obtained previously, and feedback could be provided to indicate closeness to the desired state.

In an 8080A system with 2 MHz clock, running Polymorphic Systems BASIC, classification calculations for 15 variables and five egostates took about one second per egostate. To accomplish real time physiological data analysis and classification, the use of two or more linked processors would speed this process. A floating point arithmetic processor such as the AMD 9511 could be used to speed the calculation process by at least an order of magnitude, thus permitting short latency feedback.

The use of slides from the Ego State Inventory was a compromise made in the interest of simplification. In future research, it may be possible to use the techniques of psychodrama to evoke the events of interest. This would permit the use of observers as objective judges of the presence or absence of a desired (or undesired) state; such observers could inform the computer of their judgements via keyboards. The study of states which are not objectively identifiable might proceed with subjective reports from the subject, as in the study reported here.

Movement artefacts would be a more serious problem in a psychodrama study, and would make accurate EEG data collection more difficult. But it is possible that recording body movements might yield useful data on identity states. There may be patterns which could be detected in such movements.

Speculating along the same line, period-amplitude analysis of eye movements might yield useful data regarding identity states, and should be part of any future study.

If movement artefacts are a serious problem in psychodrama, it may be possible to use guided imagery or motion pictures to evoke identity states.

Computer assisted learning (CAL) is an example of a possible application of this methodology. Pierre St. Jean (1978) has described how a CAL system could be augmented with biofeedback training. In simple CAL, the computer presents information to the student in small blocks, with questions interspersed. If the student answers a question correctly, more new material is presented, but if a question in incorrectly answered, the old material is reviewed, or sometimes presented from a new perspective.

The student's responses to these questions could be used to detect what St. Jean calls "High Learning States," those states of consciousness in which the student can learn quickly. The methodology described in this dissertation could be used to calculate discriminant coefficients for physiological identification of high learning states, drowsy states, focussed attention, etc., and the CAL system could branch from its normal flow of textual presentation into a rest period, a more arousing audio-visual presentation or even a conventional biofeedback training session, depending on the student's physiological state.

In theraputic applications, the identification of the correlates of a desired or undesired emotion or other event in consciousness would open the door to voluntary training in the control of that state. This would be of much more practical value if it turns out to be possible to use the same set of discriminant coefficients for any subject, as it would allow people skilled in attaining a desired state to produce training templates for unskilled patients or students to use. If it proves possible to reliably identify physiological patterns associated with the desire for heroin, for example, it might be possible to offer addicts training in suppression of that physiological state. Or, if it proves possible to identify the correlates of a non-attached (enlightened, desireless) state, perhaps training in attainment of that state would be possible (within the limitations of the contradiction implicit in desiring desirelessness). I do not suggest that we should work toward training for some standardized state of consciousness but rather that it would be useful to have a wider selection of states available to each person.

The use of microcomputers to generate effective feedback signals may help in pattern biofeedback training. For example, it would be possible to have a microcomputer sketch a cartoon facial expression as a feedback signal to indicate the detected identity state. A mirror for emotions would surely be a useful therapeutic tool.

Such notions are still in the category of speculation, but the possibility may exist for "decoding the body's language" by recording the correlates of many specific emotional states, and this might lead to the possibility of rich new communication modalities, ways of sharing experiences which are now locked inside each of us.

REFERENCES

Adrian, E. D. and Bronk, D. W. The discharge of impulses in motor nerve fibres. Part 1. Impulses in the single fibres of the phrenic nerve. Journal of Physiology, 1928, 66, 81-101.

Anand, B. K., Chhina, G. S. and Singh, B. Some aspects of electroencephalographic studies in yogis. Electroencephalography and Clinical Neurophysiology, 1961, 13, 3452-456.

Banquet, J. EEG and meditation. Electroencephalography and Clinical Neurophysiology, 1972, 33, 454.

Basmajian, J.V. Muscles alive. Baltimore: Williams & Wilkins, 1974.

Beatty, J. and Figueroa, C. Period analytic algorithms for the estimation of selected spectral properties of short segments of EEG data. Behavior Research Methods and Instrumentation , 1974, 6 , 293-295.

Berger, H. Uber das Elektrenkephalogramm des Menschen. Archiv fur Psychiatrie and Nervenkrankheiten , 1929, 40 , 527-570.

Berne, E. Transactional analysis in psychotherapy. New York: Ballantine Books, 1961.

Blacker, K. H., Jones, R. T., Stone, G. C. and Pfefferbaum, D. Chronic users of LSD: The "acidheads." American Journal of Psychiatry. 1968, 125 , 341-351.

Brown, B. Stress and the art of biofeedback. New York:
Harper & Row, 1977.

Buchsbaum, M. and Silverman, J. Stimulus intensity control and the cortical evoked response. Psychosomatic Medicine, 1968, 30 , 12-22.

Budzynski, T. Tuning in on the twilight zone. Psychology Today August, 1977, pp. 40-44.

Clynes, M. Recognition of visual stimuli from the electric response of the brain. In N.S. Kline and E. Laska (Eds.), Computers and electronic devises in psychiatry. New York: Grune & Stratton, 1968.

-----, Sentics: Biocybernetics of emotion communication. Annals of the New York Academy of Sciences, 1973, 220 , 57-131.

-----, Sentics: The touch of emotions . Garden City, N.Y.: Anchor Press/Doubleday, 1977.

Cohen, J. Cerebral psychophysiology: The contingent negative variation. In R. F. Thompson and M. M. Patterson (Eds.), Bioelectric recording techniques (Vol. 1-B).New York: Academic Press, 1974.

Cooley, J., Lewis, P. and Welch, P. The fast Fourier transform and its application to time series analysis. In K. Enslein, A. Ralston and H. Wilf (Eds.), Statistical methods for digital computers (Vol. 3). New York: John Wiley & Sons, 1977.

Daiment, J., Dufek, M., Hoskovec, J., Kristof, M., Pekarek, V. Roth, B., and Velek, M. An electroencephalographic study of the waking state and hypnosis with particular reference to subclinical manifestations of sleep activity. International Journal of Clinical and Experimental Hypnosis, 1960, 8 , 199.

Darrow, C.W. Sensory, secretory and electrical changes in the skin following bodily excitation. Journal of Experimental Psychology , 1927, 10 , 197-226.

Dement, W. and Kleitman, N. Cyclic variations in EEG during sleep and their relation to eye movements, body motility, and dreaming. Electroencephalography and Clinical Neurophysiology , 1957, 9 , 673-689.

Don, N. The transformation of conscious experience and its EEG correlates. Journal of Altered States of Consciousness , 1978, 3 , 147-168.

Dusay, J. M. Egograms . New York: Harper & Row, 1977.

The evolution of transactional analysis. In G. Barnes (Ed.), Transactional analysis after Eric Berne . New York: Harper's College Press, 1977.

Ertl, J.P. Using the speed of brainwaves to test IQ. Medical World News , March, 1968.

---- Evoked potential and human intelligence . Final Report, U. S. Office of Education, Project No. 6-1545, 1968.

---- Evoked potentials, neural efficiency and IQ. In L.D. Proctor (Ed.), Biocybernetics of the central nervous system . Boston: Little Brown & Co., 1969.

---- Fourier analysis of evoked potentials and human intelligence. Nature , 1971, 230 , 525-526. 126

----- IQ, evoked response and Fourier analysis., Nature , 1973, 241 , 209-210.

Fujisawa, K., Koga, E., and Toyoda, J. The polygraphical study on the psychogenic changes of consciousness. (1). about Zen, Yoga and hypnosis. Electroencephalography and Clinical Neurophysiology (Suppl.), 1959, 18 , 51.

Fuller, G. Biofeedback: Methods and procedures in clinical practice . San Francisco: Biofeedback Press, 1977.

Gananadesikan, R. Methods for statistical analysis of multivariate observations . New York: John Wiley & Sons, 1977.

Georgiou, Bill. Give an ear to your computer. Byte , 1978, 3 (6), 56-91.

Green A., and Green, E. Biofeedback: Research and therapy. In N. Jacobson (Ed.), Being well is a responsibility . London: Turnstone Books, 1975.

Green, E. and Green, A. Beyond biofeedback . New York: Dell Publishing, 1977.

Green, E., Green, A., and Walters, E.D. Voluntary control of internal states: Physiological and psychological. Journal of Transpersonal.Psychology , 1970, 2 , 1-26.

Huxley, A. The doors of perception and Heaven and hell . New York: Harper & Row, 1954.

James, W. The varieties of religious experience . New York: Collier, 1961. Originally published in 1902.

Jasper, H.H. Report of the committee on methods of clinical examination in electroencephalography. Electroencephalography and Clinical Neurophysiology , 1958, 10 , 370.

Jennrich, R. Stepwise discriminant analysis. In K. Enslin, A. Ralston and H. Wilf. (Eds.), Statistical methods for digital computers (Vol. 3) , New York: John Wiley & Sons, 1977.

John, E.R. A model of consciousness. In G. Schwartz and D. Shapiro (Eds.), Consciousness and self-regulation (Vol. 1). New York: Plenum Press, 1976.

Jung, C.G. Studies in word association . New York: Russell & Russell, 1918.

Kamiya, J. Operant control of the EEG alpha rhythm and some of its reported effects on consciousness. In C. T. Tart (Ed.), Altered States of Consciousness . New York: John Wiley & Sons, 1969.

Kamiya, J. Autoregulation of the EEG alpha: A program for the study of consciousness. In M. H. Chase (Ed.), Operant control of brain activity . Los Angeles: Brain Research Institute, University of California, 1974.

Kasamatsu, A. and Hirai, T. An electroencephalographic study on the Zen meditation (zazen). Folio Psychiatra and Neurologica Japonica , 1966, 20 , 315-336.

Krippner, S. Song of the siren . New York: Harper & Row, 1975.

Lachenbruch, P. and Mickey, M. Estimation of error rates in discriminant analysis. Technometrics , 1968, 10, 1-11.

Larsen, L. E., Ruspini, E. H., McNew, J. J., Walter, D. 0., and Adey, W. R. Classification and discrimination of the EEG during sleep. In P. Kelleway and I. Petersen (Eds.), Automation of clinical electroencephalography . New York: Raven Press, 1973.

Lilly, J. C. The center of the cyclone. New York: Julian Press, 1972.

MacLean, P. D. A triune concept of the brain and behavior . Toronto: University of Toronto Press, 1973.

McCarley, G. D. The Ego State Inventory . Chicago: Stoelting Co., 1974.

McNew, J. J., Kado, R. T., Howe, R. C., Zweizig, T. R. and Adey, W. R. Telemetry studies of sleep in the unrestrained chimpanzee. 1968 Institute of Electrical and Electronics Engineers national telemetering conference record , pp. 374-381.

Miller, N. Learning of visceral and glandular responses. Science , 1969, 163 , 434-445.

Mittlemann, B. and Wolff, H. G. Affective states and skin temperature: Experimental study of subjects with "cold hands" and Raynaud's Syndrome. Psychosomatic Medicine , 1939, 1 , 271-292.

Morrell, L. K. Some characteristics of stimulus-provoked alpha activity. Electroencephalography and Clinical Neurophysiology , 1966, 21 , 552-561.

Morrison, D. F. Multivarite statistical methods : New York: McGraw Hill, 1967.

Neumann, E. and Blanton, R. The early history of electrodermal research. Psychophysiology , 1970, 6 , 453-475.

Ouspensky, P. In search of the miraculous . New York: Harcourt, 1949.

Payne, B. and Reitario, C. BioMeditation . Brookline, Mass.: Institute for Psychoenergetics, 1977.

Penfield, W. Memory mechanisms. Archives of Neurology and Psychiatry , 1952, 67 , 178-198.

Penfield, W. and Roberts, L. Speech and brain mechanisms. New York: Atheneum, 1974.

Peper, E. Localized EEG alpha feedback training: A possible technique for mapping subjective, conscious and behavioral experiences. Kybernetik , 1972, 11 , 166-169.

Phares, E. Locus of control in personality . Morristown, New Jersey: General Learning Press, 1976.

Reich, W. Character analysis (3rd ed.). New York: Orgone Institute Press, 1949.

Sagan, C. The dragons of Eden . New York: Ballantine, 1977.

Schwartz, G. E. Biofeedback, self-regulation and the patterning of physiological processes. American Scientist , 1975, 63 , 314-324. Reprinted in T. X. Barber, L. V. DiCara, J. Kamiya, N. E. Miller, D. Shapiro and J. Stoyva (Eds.), Biofeedback and self control 1975/76 . Chicago: Aldine Publishing, 1976.

Skinner, B. F. Beyond freedom and dignity . New York: Bantam, 1971.

---- About behaviorism . New York: Alfred A. Knopf, 1974.

Sterman, M. B. and Friar, L. Suppression of seizures in an epileptic following sensorimotor EEG feedback training. Electroencephalography and Clinical Neurophysiology , 1972, 33 , 89-95.

Stoyva, J. M. and Kamiya, J. Electrophysiological studies of dreaming as the prototype of a new strategy in the study of consciousness. Psychophysiological Review , 1968, 75 , 192-205.

Strobel, C. F. and Glueck, B. C. Biofeedback treatment in medicine and psychiatry: An ultimate placebo? In L. Birk (Ed.), Biofeedback: Behavioral medicine . New York: Grune & Stratton, 1973.

Tart, C. T. States of consciousness . New York: Dutton, 1975.

Taylor, F. and Abraham, P. A search for a safe bentonite paste. Electro-Physiological Technologists Association Proceedings , 1969, 16 , 269.

Walter, W. G. The living brain . New York: Norton, 1963.

Webb, C. The use of myoelectric feedback in teaching facial expression to the blind. Biofeedback and Self-Regulation , 1977, *2* , 147-160.

Wickramasekera, I. Biofeedback, behavior therapy and hypnosis: Convergences and the placebo response. In I. Wickramasekera (Ed.), Biofeedback, behavior therapy and hypnosis , Chicago: Nelson-Hall, 1976.

Wolpe, J. The practice of behavior therapy (2nd ed.). New York: Pergamon Press, 1973.

Wooldridge, D. E. The machinery of the brain . New York: McGraw Hill, 1963.

Zetterberg, L. H. Experience with the analysis and simulation of EEG signals with parametric description of spectra. In P. Kellaway and I. Petersen (Eds.), Automation of clinical electroencephalography . New York: Raven Press, 1973.

Unpublished References

Ancoli, S. and Kamiya, J. Methodological issues in alpha biofeedback training-. Paper presented at the Biofeedback Society of America eighth annual meeting, Orlando, Florida, March 1977.

Budzynski, T. Anxiety and psychological stress: A biofeedback approach . A training workshop for professionals sponsored by the Biofeedback Society of America, Avalon, Catalina Island, California, October 1977.

Don, N. Cortical activity changes during a psychotheraputic procedure: Implications for EEG biofeedback training . Paper presented at the Biofeedback Research Society sixth annual meeting, Monterey, California, February 1975.

Glaros, A. Subjective reports in alpha feedback training . Paper presented at the Biofeedback Society of America eighth annual meeting, Orlando, Florida, March 1977.

Glaros, A., Freedman, R. and Foureman, W. C. Effects of percieved control on subjective reports in alpha feedback training . Paper presented at the Biofeedback Society of America eighth annual meeting, Orlando, Florida, March 1977.

Hart, J. Discussion of "EEG alpha learning: State of the art" . A panel at the Biofeedback Research Society sixth annual meeting, Monterey, California, February 1975.

Lebow, K. and Allen, B. Finding a cure for treatment . Lompoc Federal Correctional Institution, Drug Abuse Program, Lompoc, California, 1974. (mimeographed article)

Mayo, J., Targ, R., and Hurt, D. Biofeedback training for bilateral EEG synchronization of individuals and subject pairs . Paper presented at the Biofeedback Research Society sixth annual meeting, Monterey, California, February 1975.

Mikuriya, T. H.. Interhemispheric alpha synchronization . Berkeley, California: 41 Tunnel Road, 94705, February 1978. (mimeographed article)

Pinneo, L. R. and Hall, D. J. Feasibility study for the design of a biocybernetic communication system . Stanford Research Institute final technical report, SRI project LSU-1936-NS. Menlo Park, California, 1975.

Plotkin, W. R. Occipital alpha and the "alpha experience" . Paper presented at the Biofeedback Research Society sixth annual meeting, Monterey, California, February 1975.

Rugh, J. Learning differential control of balanced orofacial muscles . Paper presented at the Biofeedback Society of America eighth annual meeting, Orlando, Florida, March 1977.

Scully, T. A 128 point amplitude-frequency histogram algorithm for real-time EEG analysis . Fifth trimester report to HPI, San Francisco, 325 Ninth Street, 94103, 1976. (mimeographed article)

------- Visual image desensitization pilot study . Sixth trimester report to HPI, San Francisco, 325 Ninth Street, 94103, 1977. (Mimeographed article)

St. Jean, P. Biosystem, systems planning . Ottawa, Ontario: Algonquin College, 1978 (mimeographed report).

Suter, S., Francoli, S., Johnson, T., and Smith, D. Independent biofeedback control of EEG alpha and skin conductance . Paper presented at the Biofeedback Society of America eighth annual meeting, Orlando, Florida, March 1977.

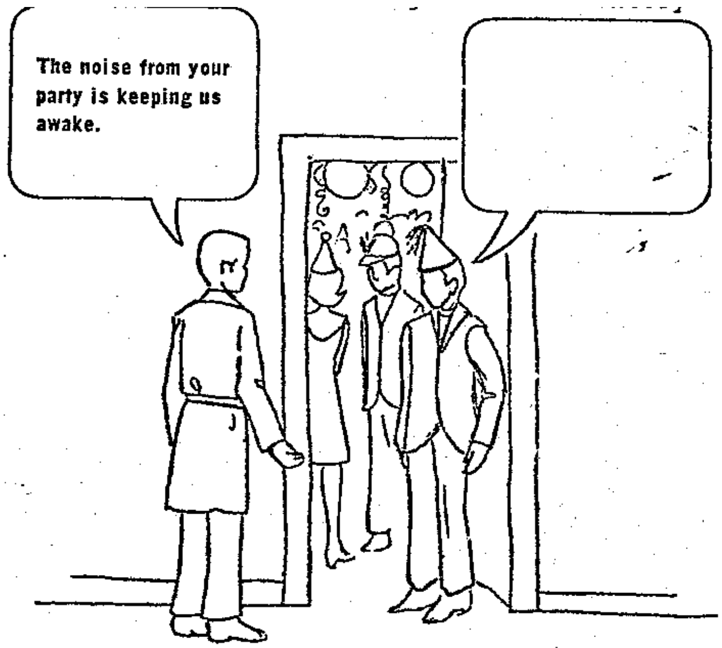
Toomim, M. K. & Toomim, H. GSR biofeedback response patterns in psychotherapy . Los Angeles: Biofeedback Research Institute, 1976. (mimeographed article).

Tyson, P. D. and Audette, R. The controversy over the relationship between alpha waves and experience during feedback . Paper presented at the Biofeedback Society of America eighth annual meeting, Orlando, Florida, March 1977.

Weber, E. and Fehmi, L. The theraputic uses of EEG biofeedback . Paper presented at the Biofeedback Research Society fifth annual meeting, Colorado Springs, Colorado, 1974. Cited in B. Brown, Stress and the art of biofeedback , New York: Harper & Row, 1977, p163.

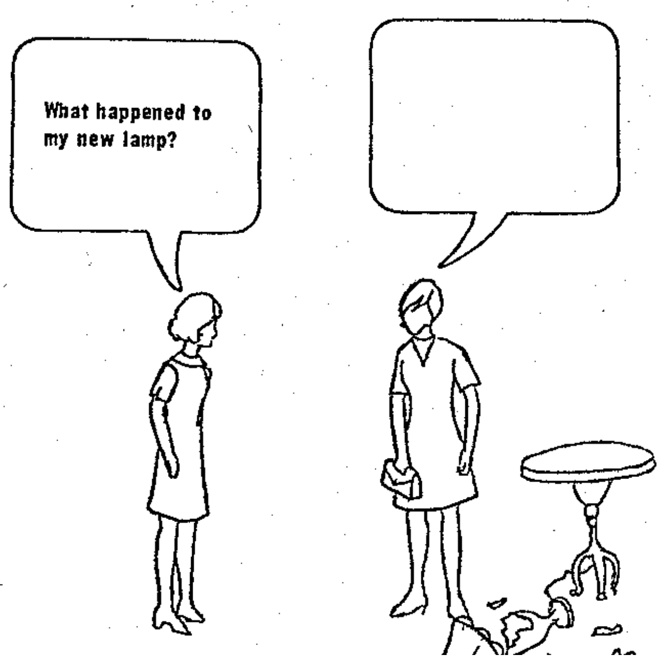
Appendix A The Ego State Inventory

1



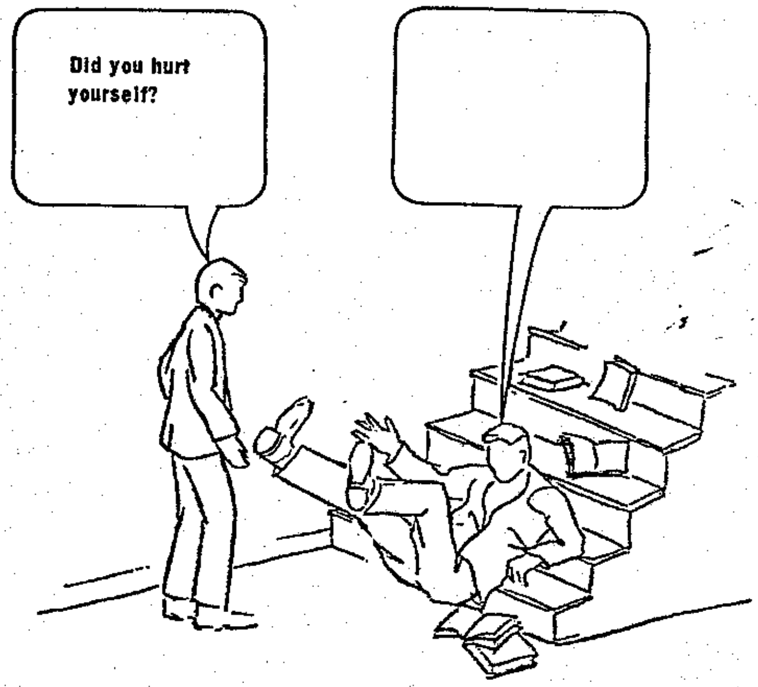
1. Get lost and mind your own business.
2. We would like to have you come in and join us.
3. Would you like to speak to the host?
4. Who cares?
5. I'm sorry. I will turn down the music right now.

2



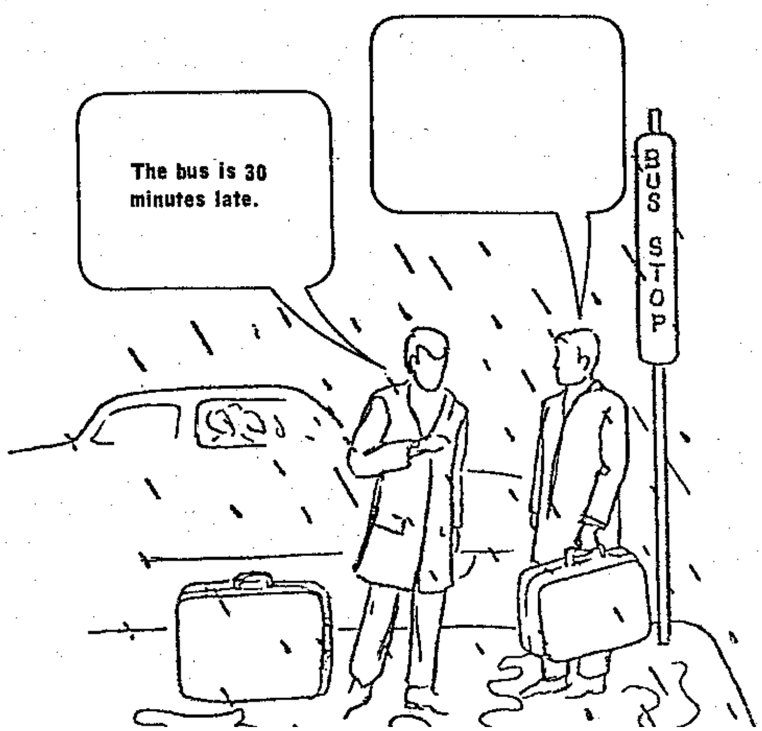
1. I'll clean it up. I should be more careful.
2. Why ask me?
3. Don't worry. I'll replace it immediately.
4. You shouldn't have had it so close to the edge.
5. I knocked it over.

3



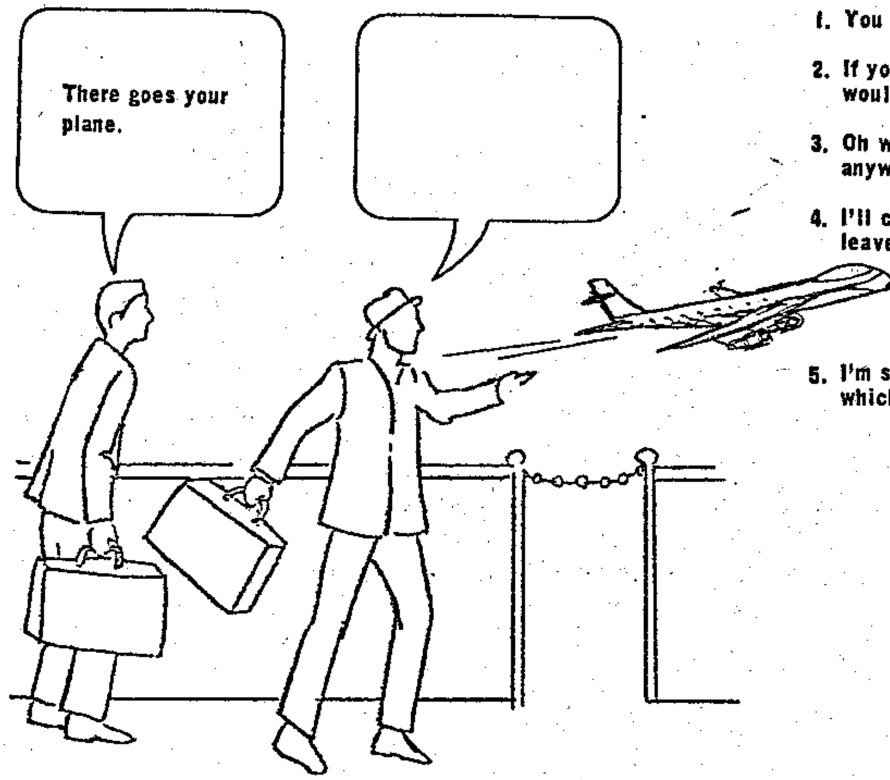
1. I'm not sure but thanks for your interest.
2. No, I don't think so.
3. What does it look like?
4. I told you to help me carry the books.
5. I just hope I didn't damage your books.

4



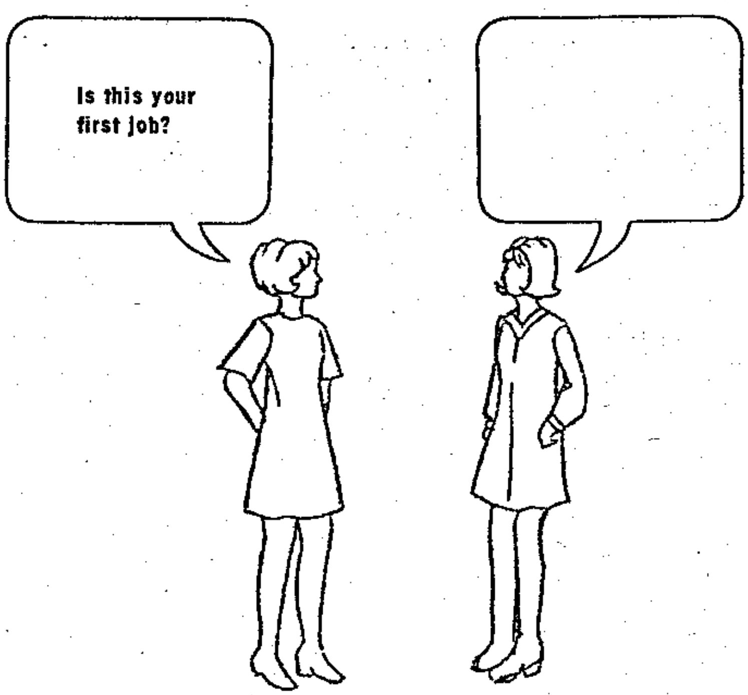
1. Well, I'm not standing here another minute.
2. I guess we will just have to put up with it.
3. It may be because of the weather.
4. You had better button your coat or you will catch a cold.
5. Stop complaining.

5



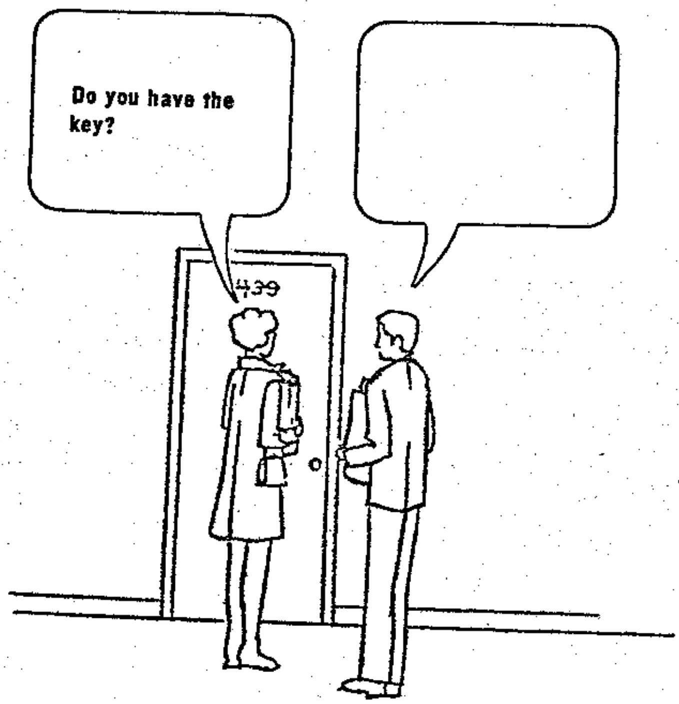
1. You don't have to tell me. I can see.
2. If you had checked on the time, this would not have happened.
3. Oh well, I didn't really want to go anyway.
4. I'll check to see when the next one leaves.
5. I'm sure there will be another one which leaves shortly.

6



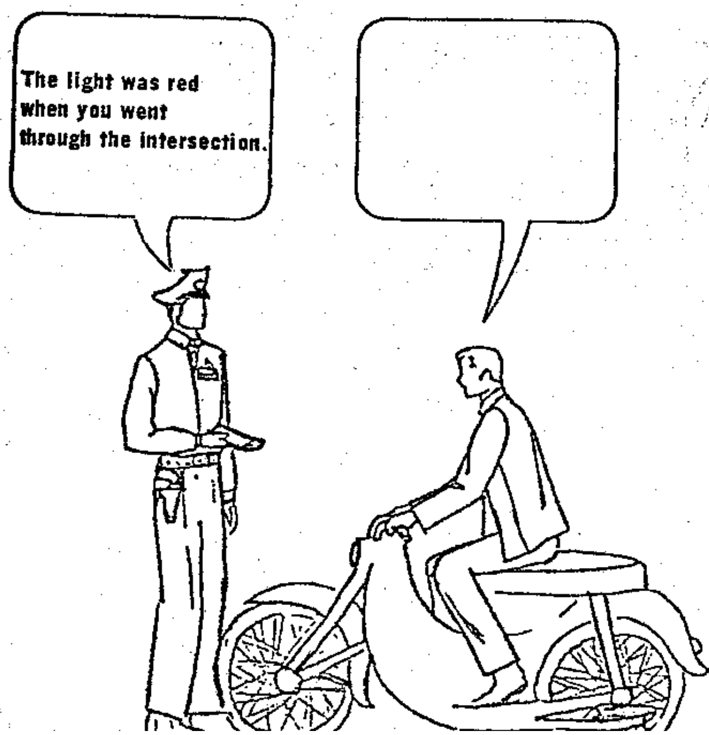
1. Yes, would you help me if I don't understand something?
2. What business is it of yours?
3. Yes, I started work yesterday.
4. No, but <u>you</u> act like it is <u>your</u> first job.
5. Yes, it is nice of you to ask.

7



1. You are always forgetting the key.
2. Why should I have it?
3. I hope I haven't lost it.
4. Yes, I think I have it.
5. Yes, let me open the door for you.

8

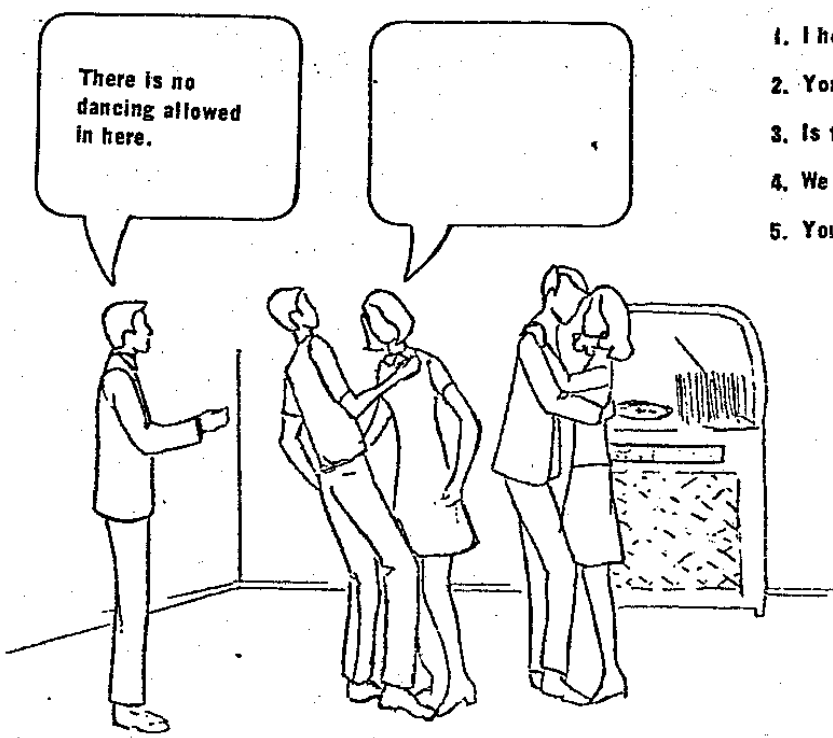


1. And I say it wasn't.
2. It's okay. I understand that you have to give me a ticket.
3. Don't you have anything better to do than hand out tickets?
4. I didn't notice that it had changed.
5. I'll be more careful next time.

9

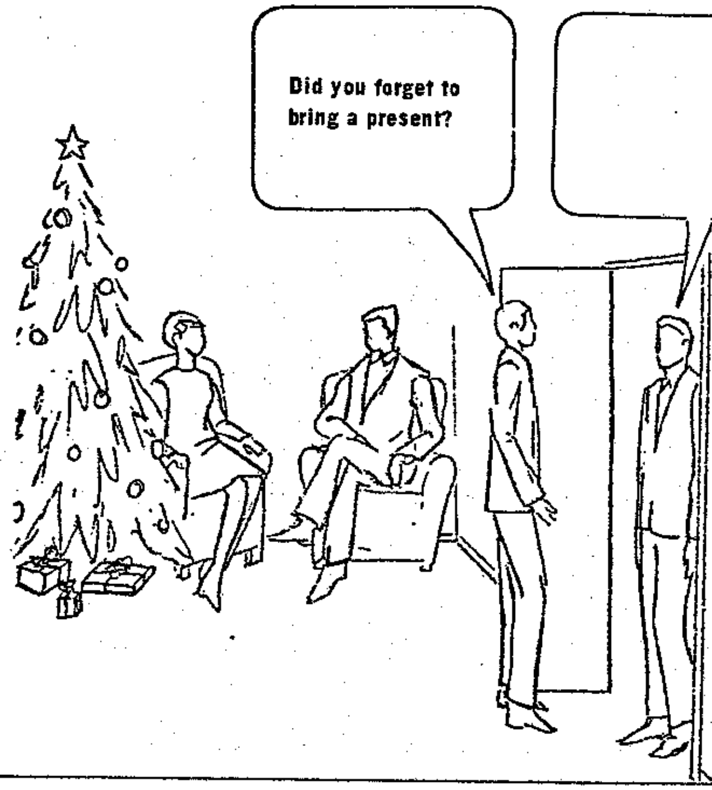
1. I guess I need the exercise anyway.
2. Someone is going to be sorry about this.
3. Well, I'm not going to carry these up 20 floors.
4. Where are the stairs?
5. Thanks, you saved me a long wait.

10



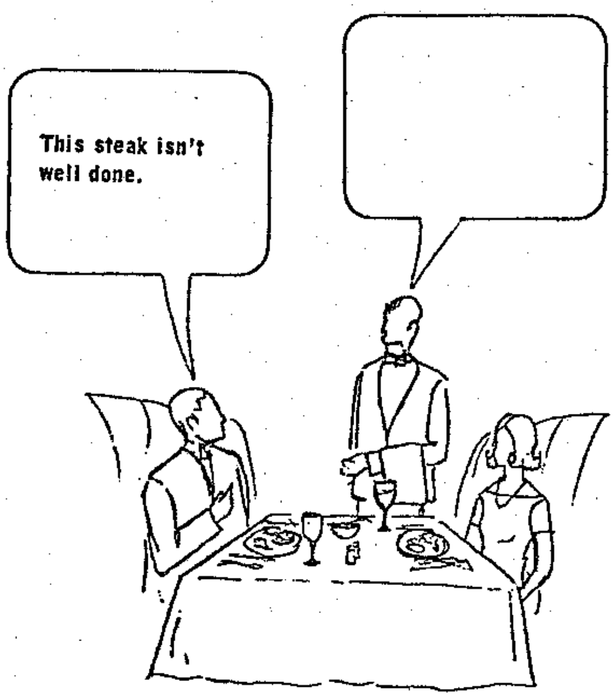
1. I hope we haven't disturbed anyone.
2. You can't stop us.
3. Is there somewhere we can dance?
4. We had better do what he says.
5. You stop bothering us!

11



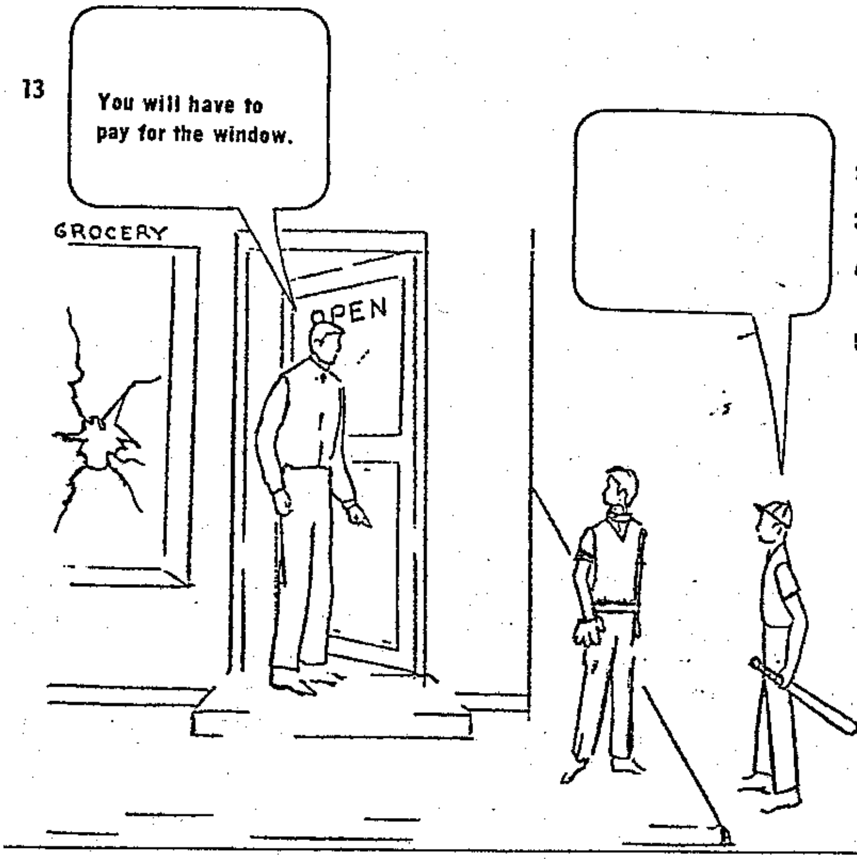
1. You should know better than to ask a question like that.
2. No, and I don't have to.
3. I didn't know presents were expected.
4. No. Your idea of exchanging presents is a great idea.
5. Yes, but I'll go get one

12



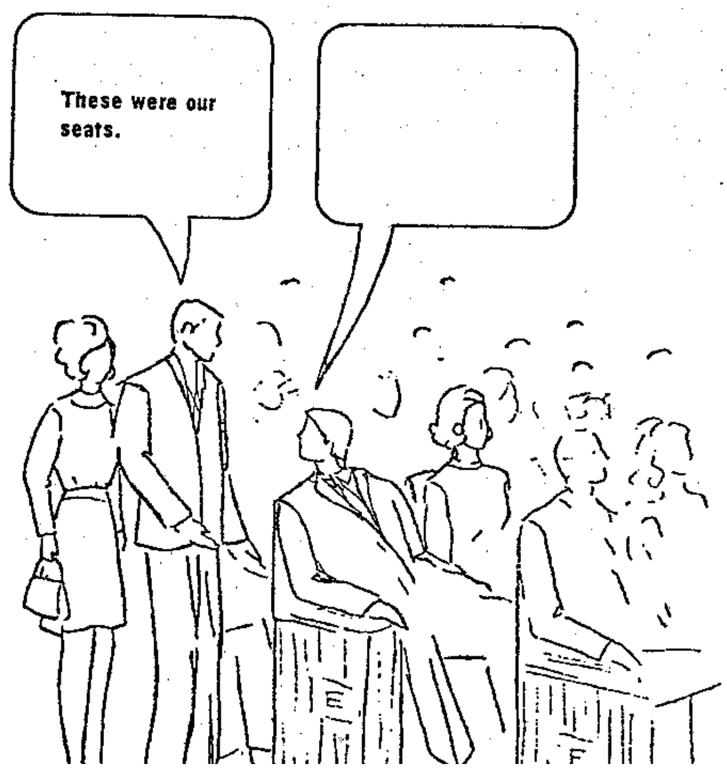
1. Please let me return it. Our duty is to please our customers.
2. I will take it back.
3. If you don't like it, go somewhere else.
4. I'm sorry. I hope the delay won't inconvenience you.
5. What do you expect me to do about it?

13



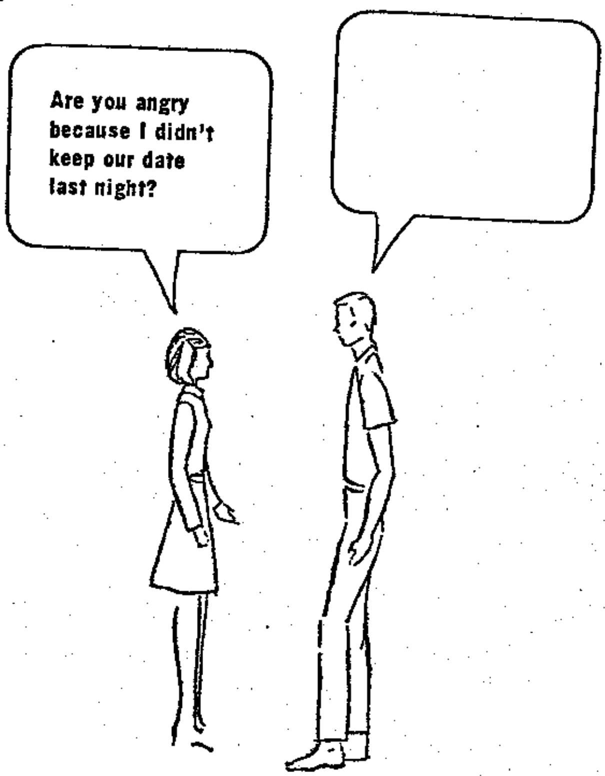
1. I hit it harder than I expected to.
2. I hope no one was hurt.
3. Try and make us.
4. We will pay for it and never play here again.
5. You should have had a screen on that window.

14



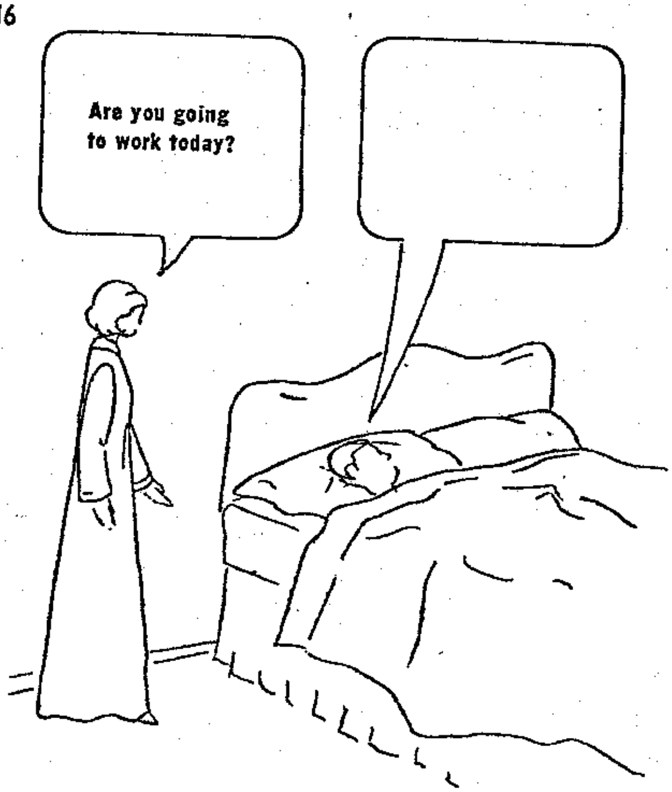
1. Prove it.
2. I'm sorry. I'll call the usher who will help you find some others.
3. Let's check our tickets.
4. Oh, I'm sorry. Then we will move.
5. You are late so take what you can find.

15



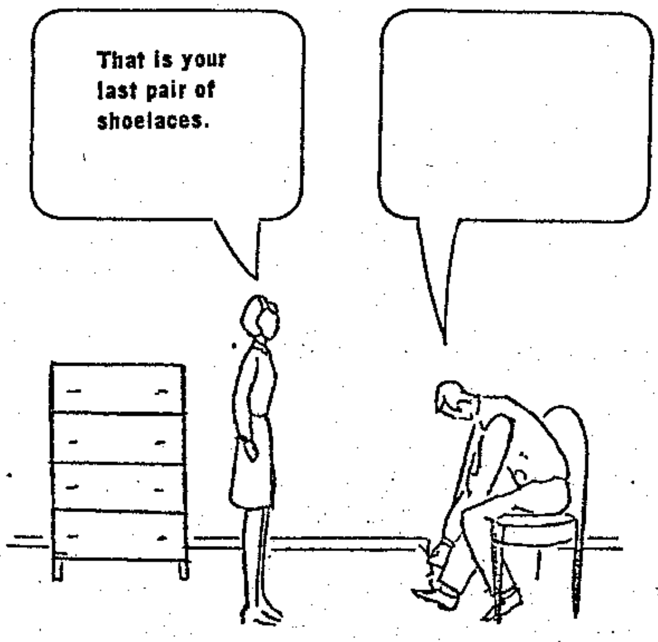
1. Things like that just happen.
2. No, I'm sure that you must have had something important to do.
3. What happened?
4. What do you think?!
5. If you had any manners you would have called.

16



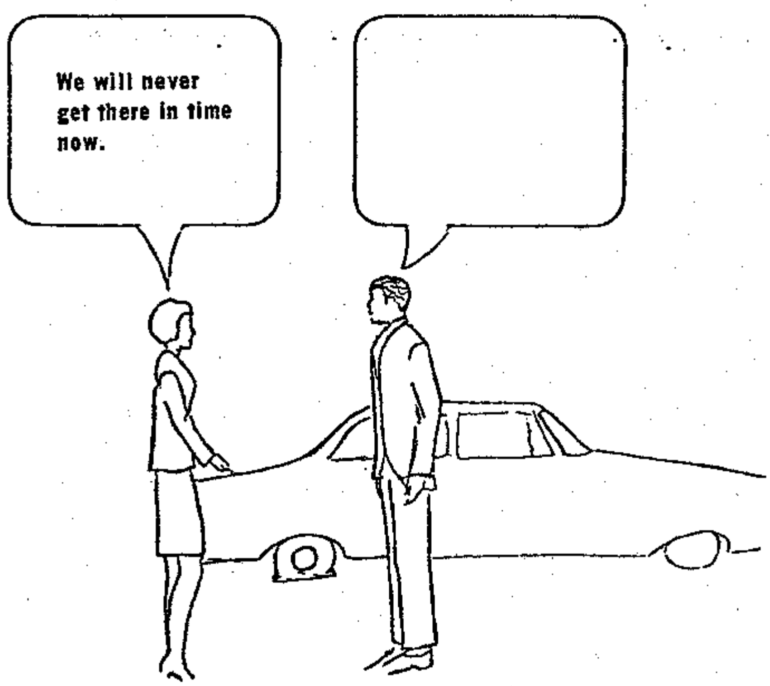
1. None of your business.
2. I told you not to wake me this morning.
3. I don't really feel like it, but I guess I'll have to.
4. Thank you for remembering to wake me.
5. Yes, what time is it?

17



1. Why didn't you buy me some more like I asked?
2. I'll buy some more later.
3. I should have listened to you and gotten some more.
4. Don't you think I know that?!
5. That's okay. Don't you worry about it.

18



1. It will take about 20 minutes to fix.
2. I should have listened to you and left earlier.
3. I'll call a taxi for you so you won't have to miss the movie.
4. It's your fault. You should have been more careful.
5. What do you expect me to do?

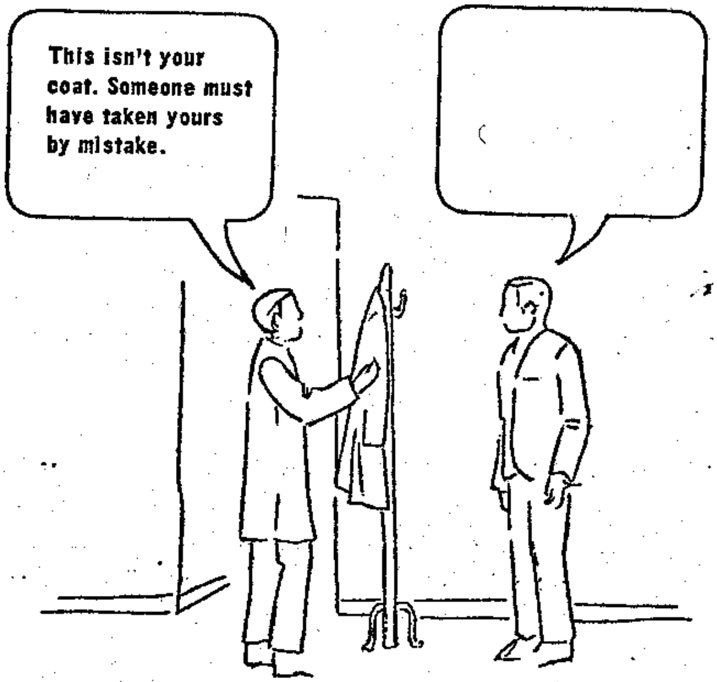
19

1. Let's go explain what happened.
2. Yes, it is the thing that we should do.
3. Are you nuts? Let's get out of here.
4. It's your fault. <u>You</u> tell them.
5. It's okay. I'll help you pay for it.

20

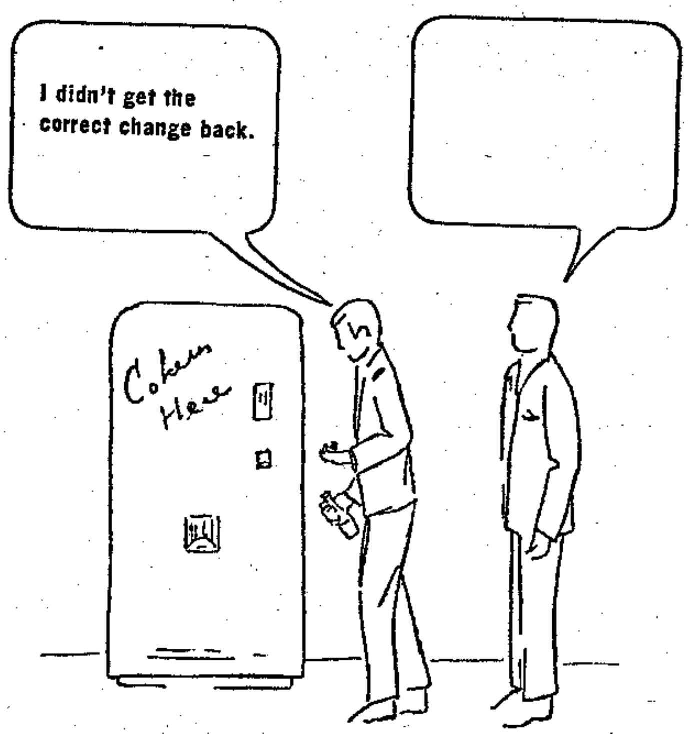
1. Those signs don't mean anything.
2. Don't tell me. I can read.
3. Oh, I hadn't noticed.
4. Oh, I'll put my cigarette out right away.
5. Oh, I'm sorry. I hope the smoke hasn't bothered you.

21



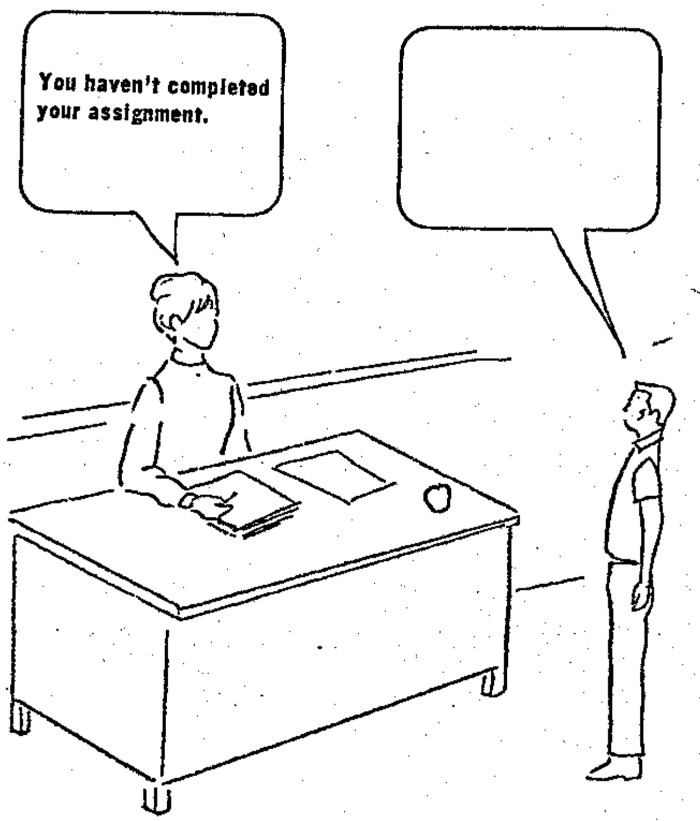
1. Well, I'm going to take theirs.
2. Why didn't you tell me sooner?
3. I should be more careful where I leave my coat.
4. Is there any identification in this one?
5. Don't worry. I'm sure I will get it back.

22



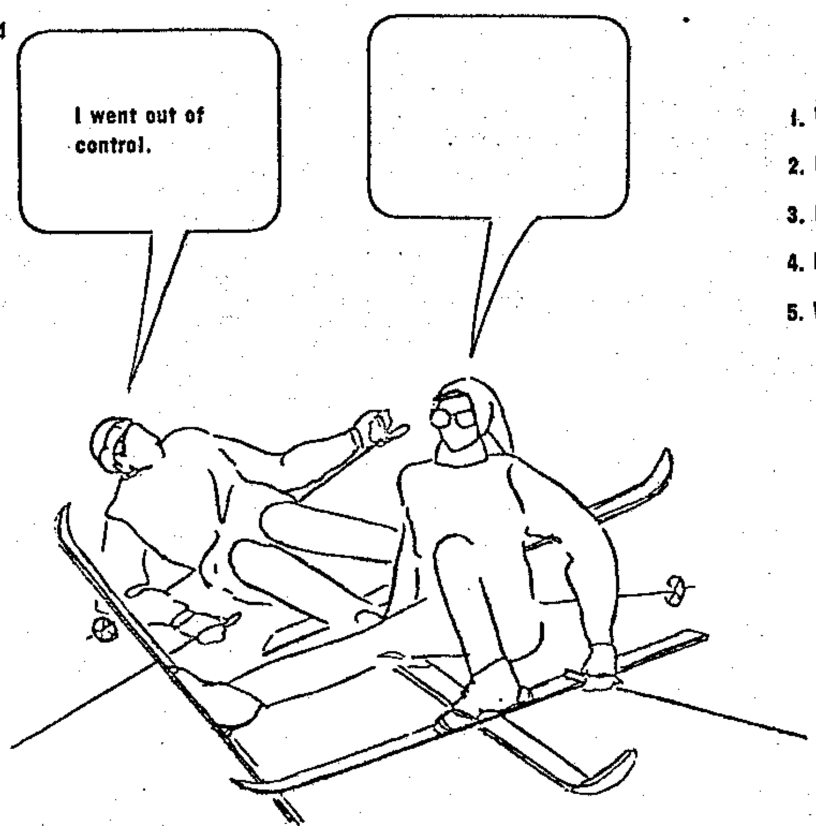
1. Why tell me?
2. Don't complain. They only cost 10¢.
3. I hope you didn't lose too much.
4. There is a number to call for a refund.
5. There is not much you can do about machines.

23



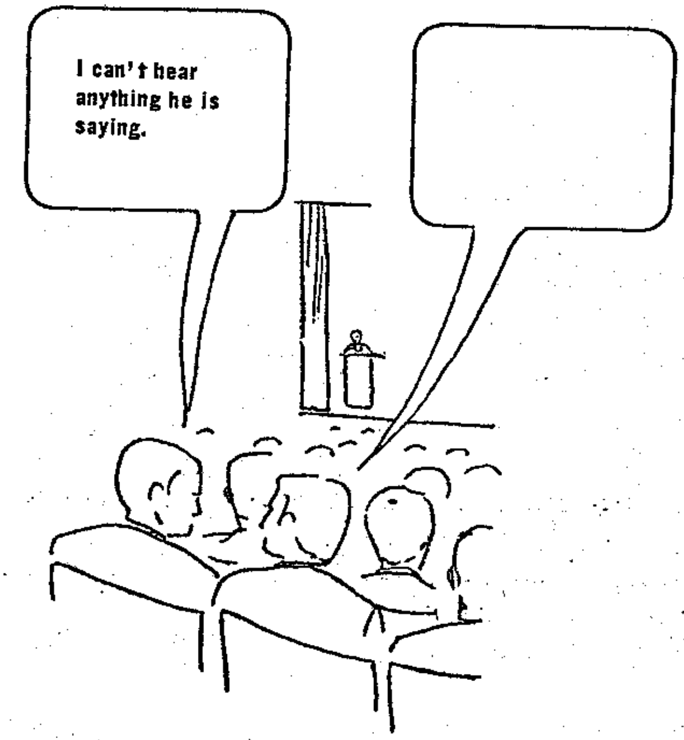
1. You shouldn't have given us so much to do.
2. So expel me.
3. Is there something else I could do?
4. I promise I'll do it tonight.
5. I didn't understand it.

24



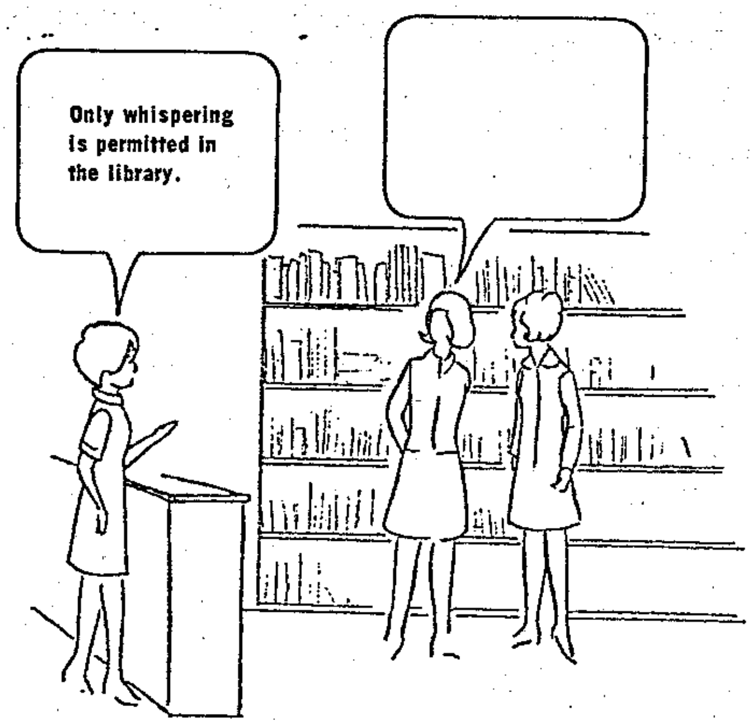
1. Well, do it somewhere else next time.
2. I hope you didn't hurt yourself.
3. No kidding!
4. I should have been watching.
5. We are lucky not to be hurt.

25



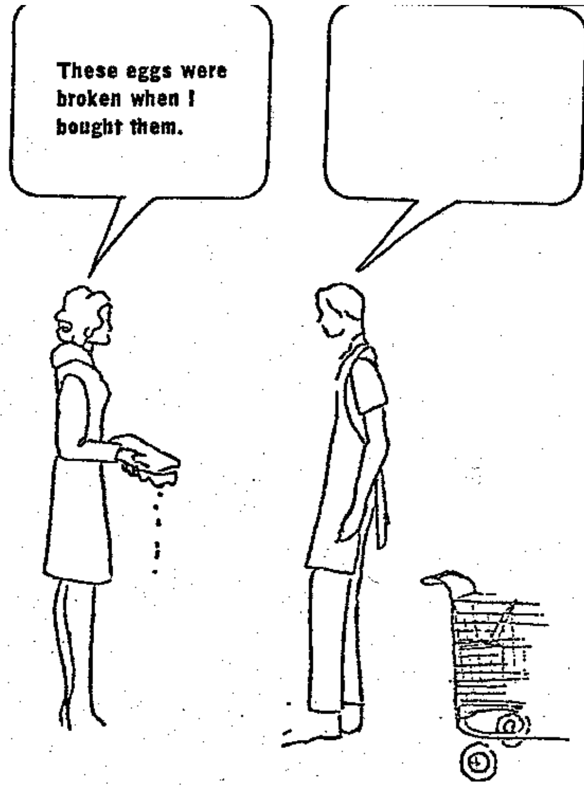
1. If you would be quiet, you could.
2. We are too far back in the auditorium.
3. Let's sit here anyway. We can ask others what he said.
4. Can I do something to help?
5. It isn't worth hearing anyway.

26



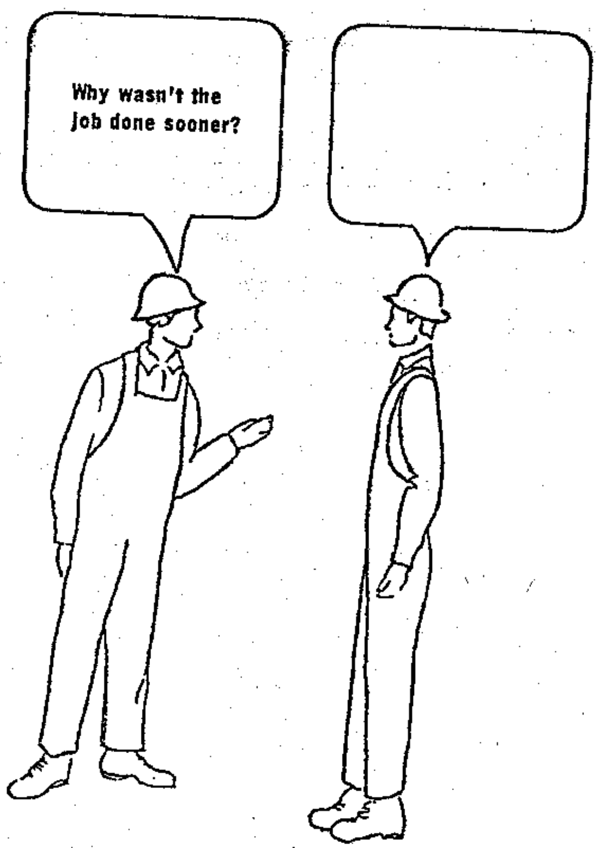
1. It is nice of you to let us know.
2. This is important. Don't interrupt us.
3. Is there a room where we can talk?
4. We are sorry that we broke the rule.
5. The same goes for you.

27



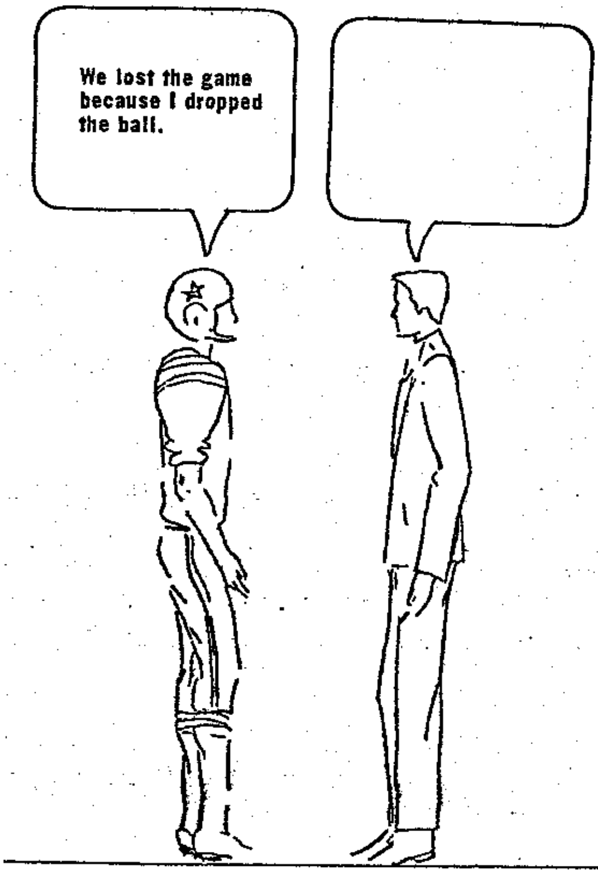
1. That's a likely story.
2. I'm sorry you had to make an extra trip.
3. I can exchange them for you.
4. You should have said something before you left the store.
5. I should have checked them more carefully.

28



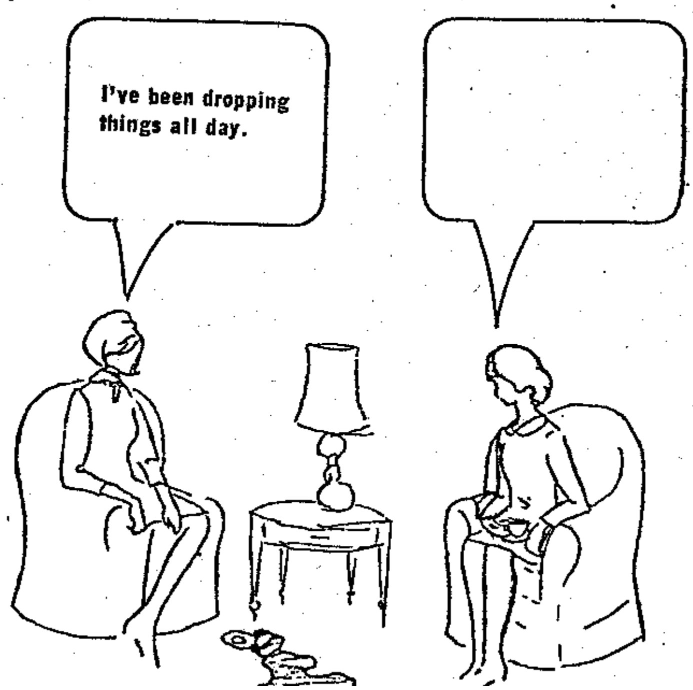
1. If you were a good foreman it would be.
2. Don't worry. We will do it for you before the deadline.
3. We are going as fast as we could, sir.
4. The materials didn't arrive in time.
5. What do you think I am, a magician?

29



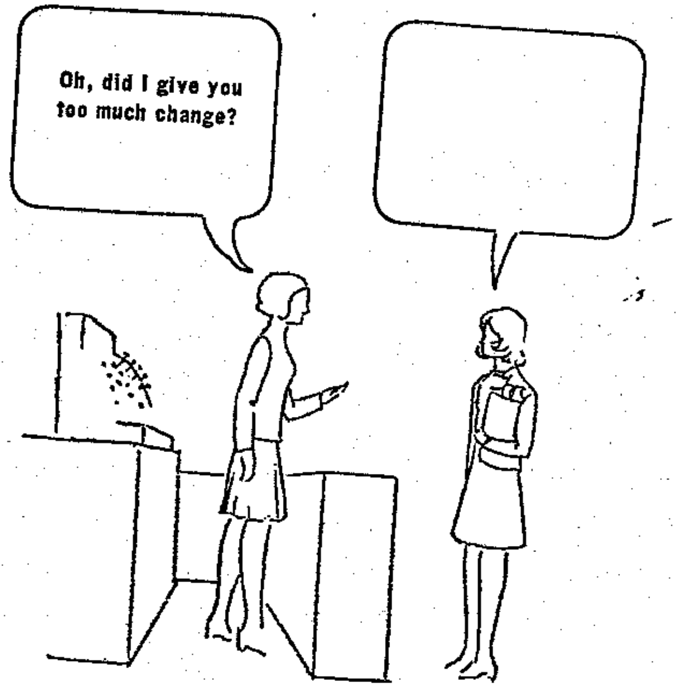
1. Well, when are you going to learn to hold onto it?
2. What do you want me to do?
3. That's okay. Everyone makes mistakes.
4. They have a very powerful team.
5. Oh well, we did what we could.

30



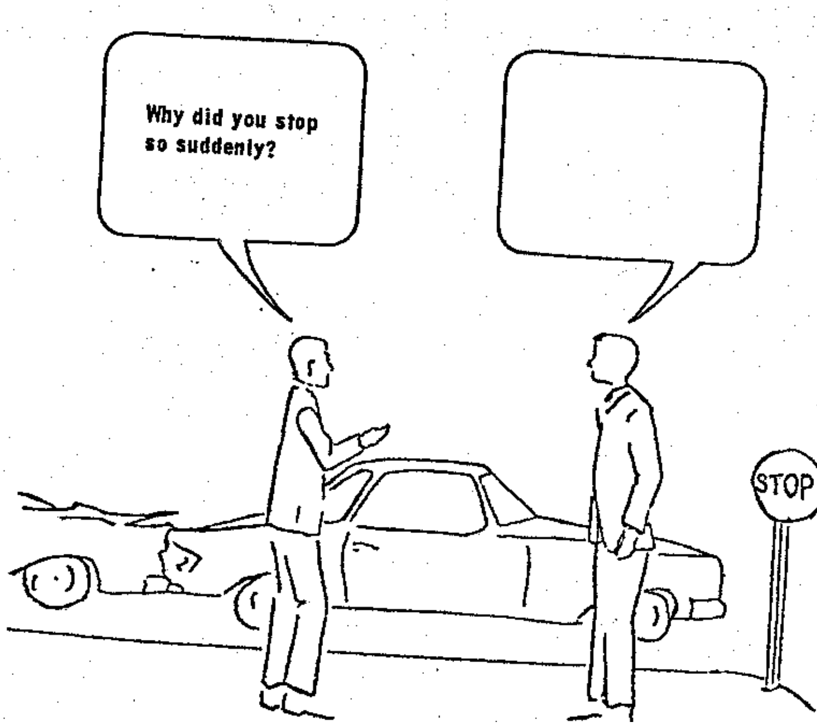
1. I'll have it cleaned up in a minute.
2. We all have days like that sometimes.
3. How sloppy can you get?
4. You're telling me!
5. Is something bothering you?

31



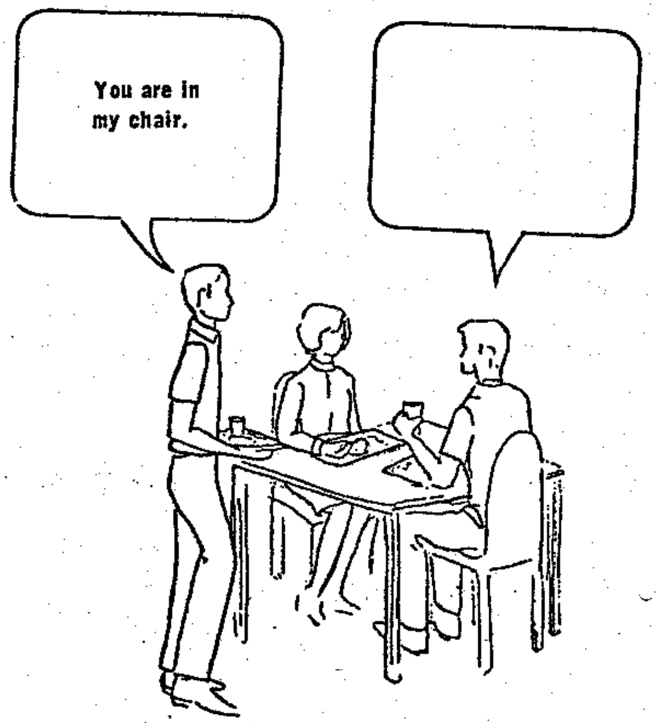
1. If you did, it's your tough luck.
2. I should have been watching more closely.
3. Yes, but don't worry, I will give it back.
4. Let me see.
5. You should know what you are doing.

32



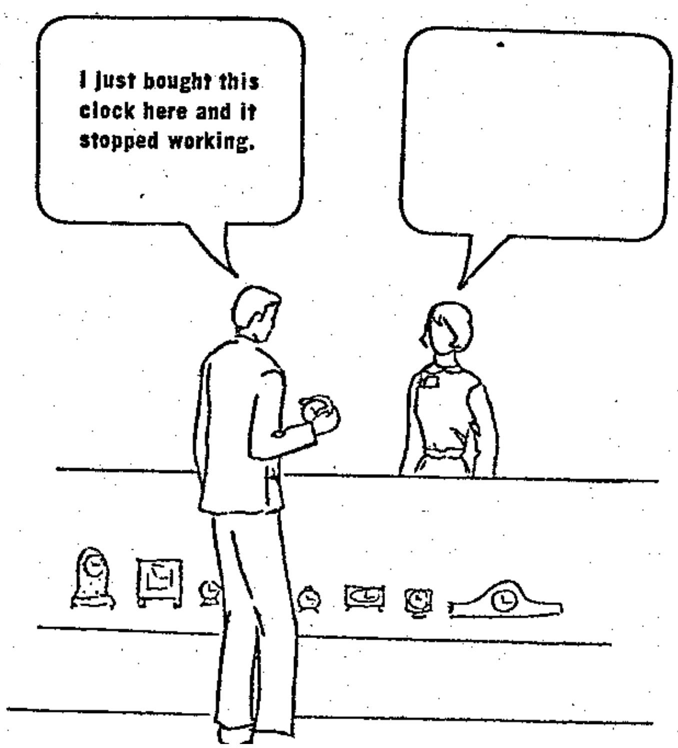
1. I guess it was my fault.
2. A dog dashed out in front of me.
3. You shouldn't be allowed to drive.
4. I hope you are not hurt.
5. I don't have to answer you.

33



1. Here, I'll get you a chair.
2. Were you here before?
3. I'll move; here is your chair.
4. You ought to find someplace else.
5. Try and move me.

34

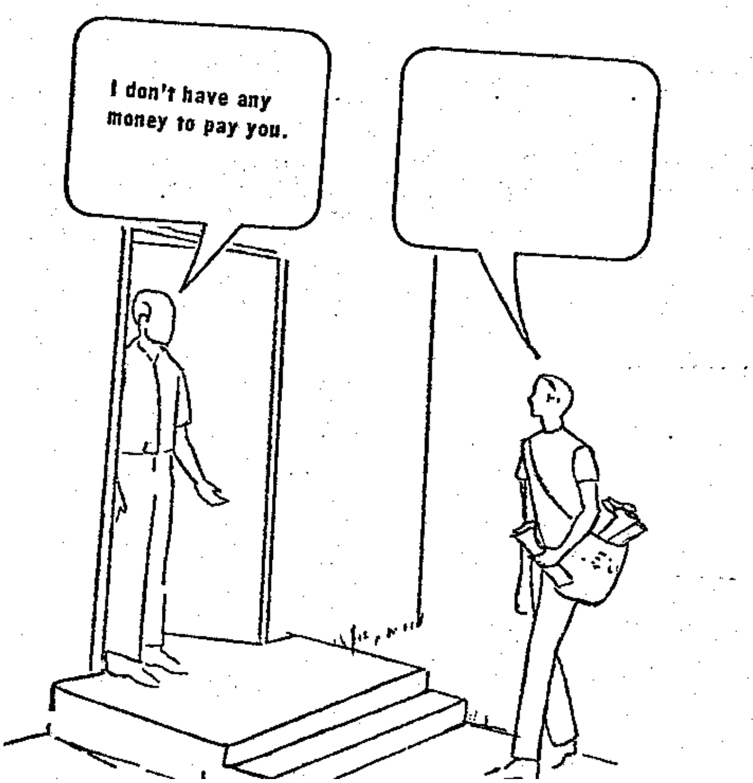


1. You probably broke it yourself.
2. Tell me what you would like us to do.
3. I'm sorry for the inconvenience.
4. What do you expect <u>me</u> to do?
5. What seems to be the trouble?

35

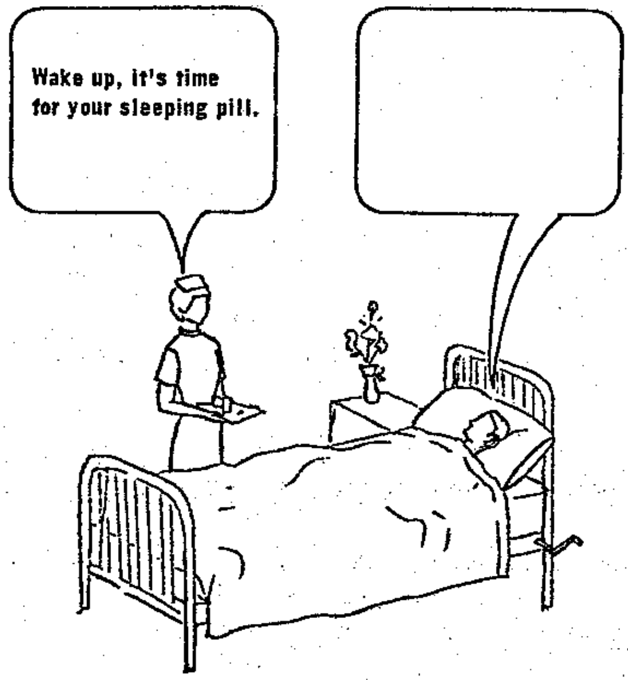
1. I will check it with the office.
2. Don't blame me.
3. You are always trying to get something for nothing.
4. You are probably right. It sounds too high.
5. If that is too much, perhaps we can reduce the bill.

36



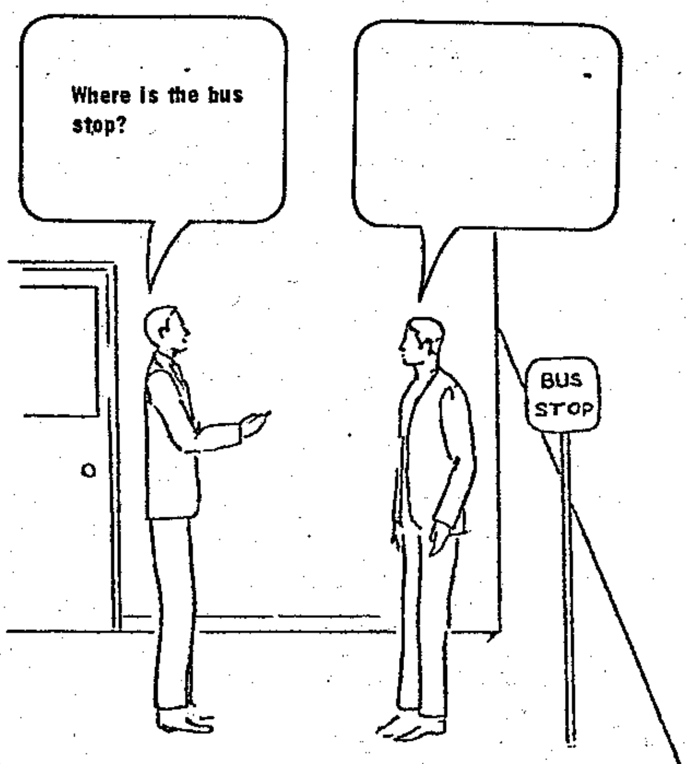
1. When would you like me to be come back?
2. That's okay. Everyone is short on money at times.
3. I want the money now.
4. You are always saying you don't have any money.
5. I will come back tomorrow.

37



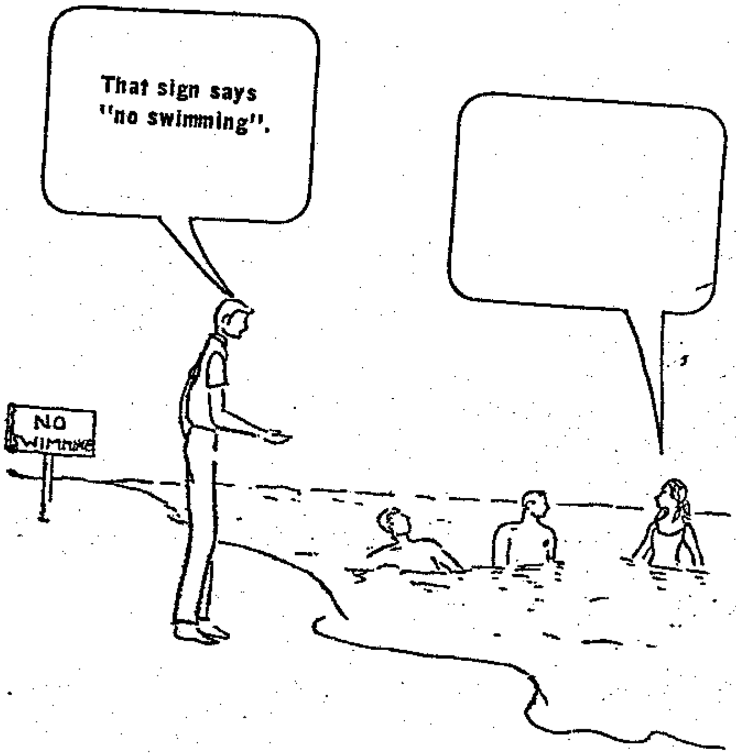
1. Now that is really stupid.
2. I have already had one.
3. Thanks. I wasn't really sleeping. This pill will help me.
4. If you think I need it, I'll take it.
5. I don't want any pills.

38



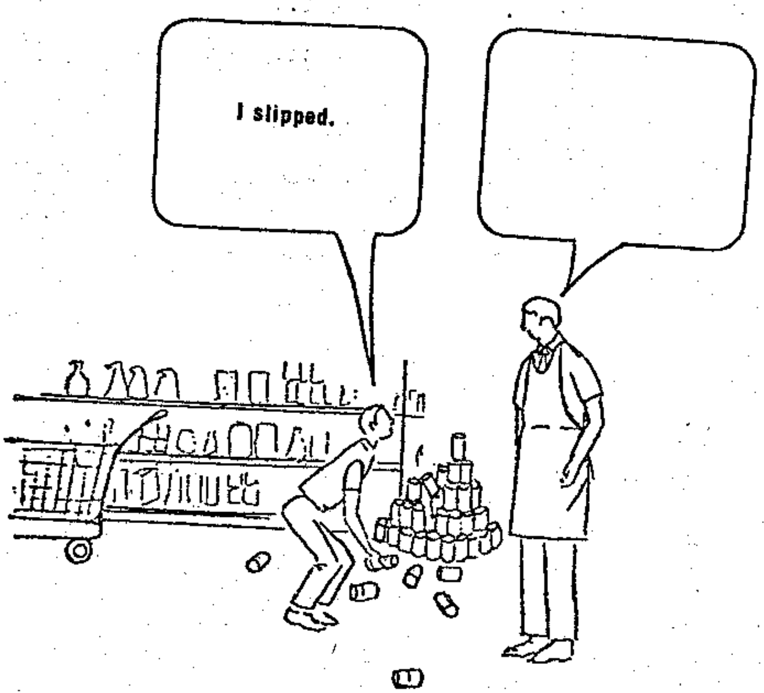
1. Here it is.
2. Don't ask me!
3. It's right here. We can catch it together
4. You should know; it's right in front of you.
5. I'm sorry, I must have been in front of the sign.

39



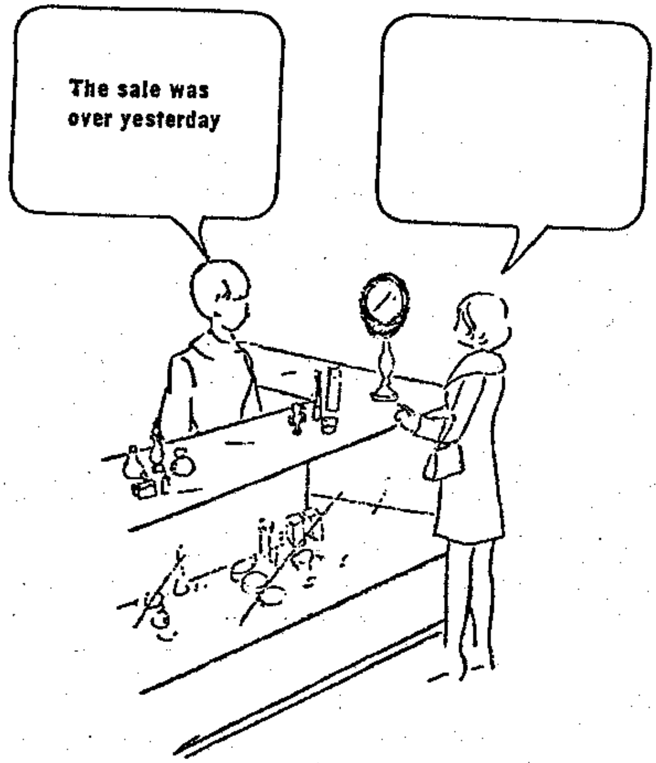
1. We have permission from the owner.
2. Who cares.
3. Please don't report us. We'll get out.
4. Do you always tell everyone what to do?
5. Thanks for taking the trouble to stop and tell us.

40



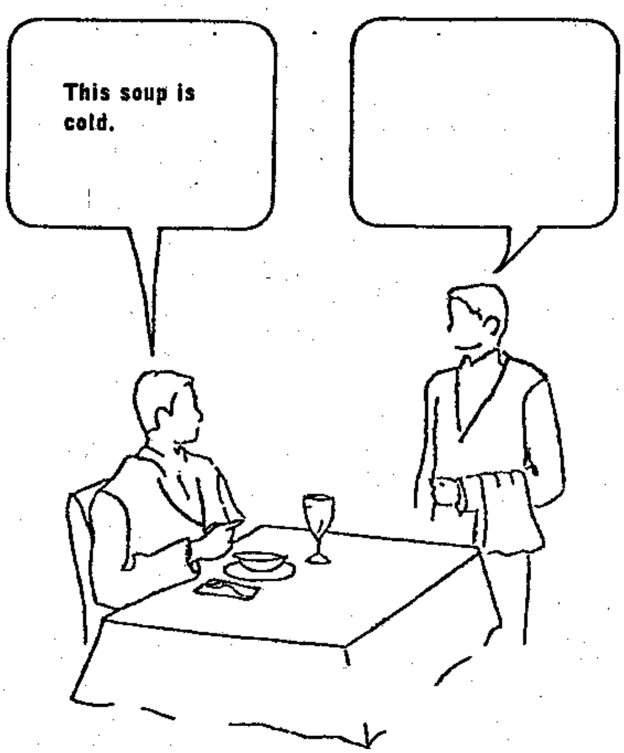
1. Are you okay? I hope you didn't hurt yourself.
2. I'm sorry, they shouldn't have been in the aisle.
3. What happened?
4. Well, I'm glad that is all the damage you did.
5. Well, it's not my fault.

41



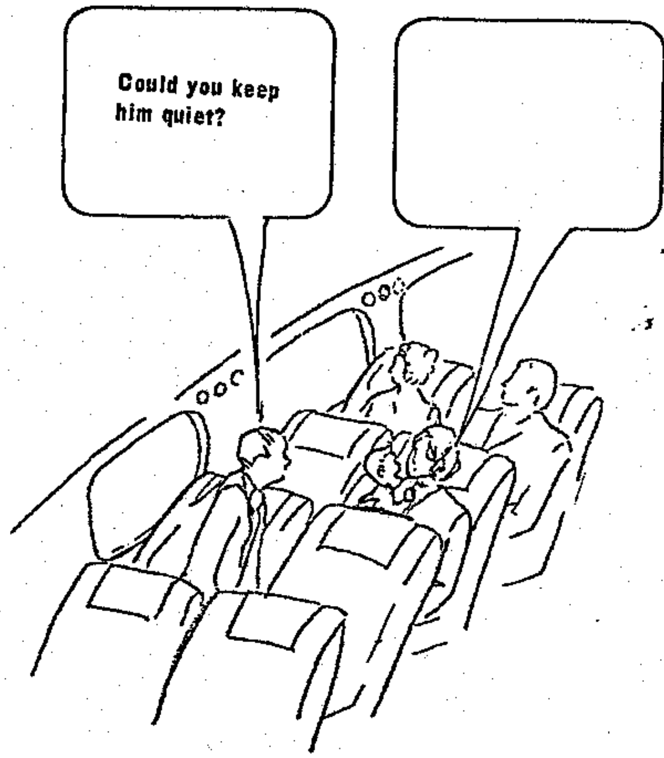
1. You are very kind to tell me before I buy.
2. How much does it cost today?
3. The days for the sale should have been advertised more clearly.
4. Sell it to me anyway. Nobody is looking.
5. Well, I guess I'll have to do without it.

42



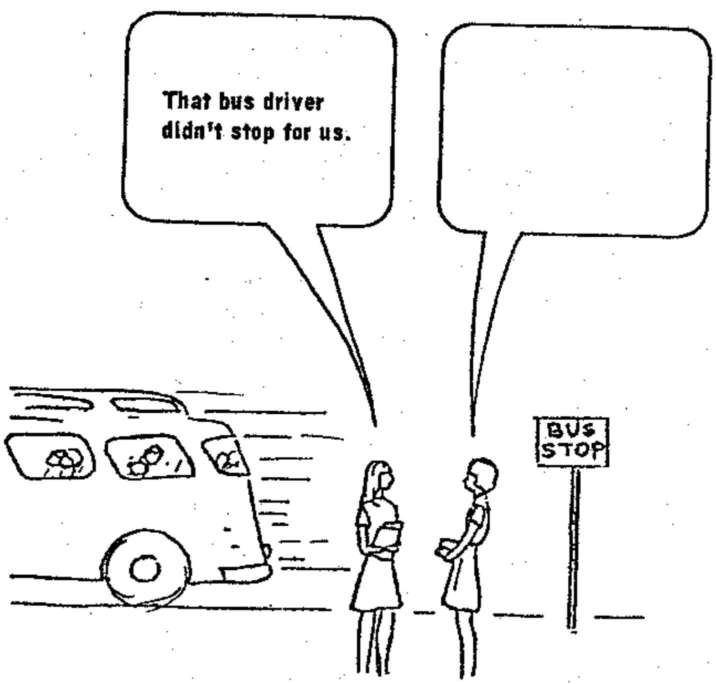
1. Would you like another bowl of soup?
2. That's too bad. I'll get you some more.
3. Well, I can't serve everybody at once.
4. It's your fault then. It was hot when I brought it.
5. I'm sorry. I should have brought it sooner.

43



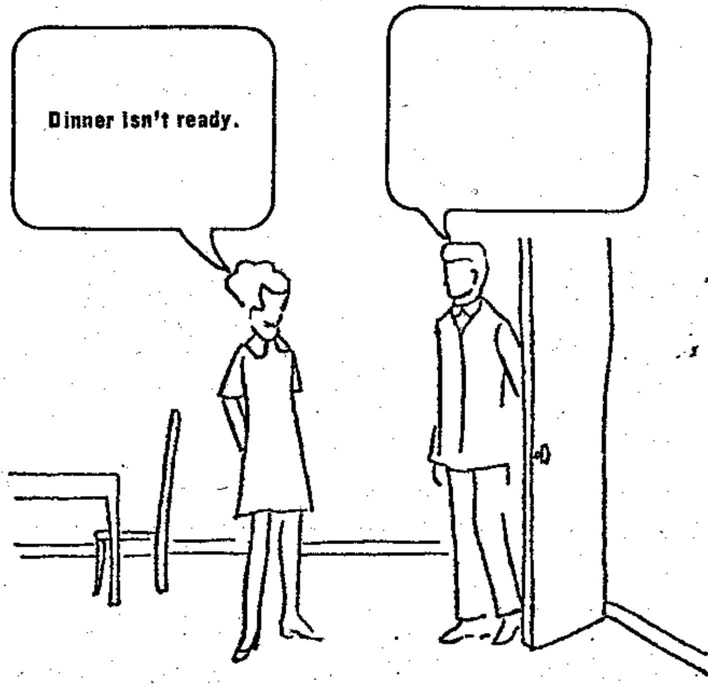
1. I'm sorry. I'll try my best.
2. You keep quiet yourself.
3. What do you expect me to do about it?
4. He is tired and not used to all the excitement.
5. I'm sorry. I hope you will be able to go back to sleep soon.

44



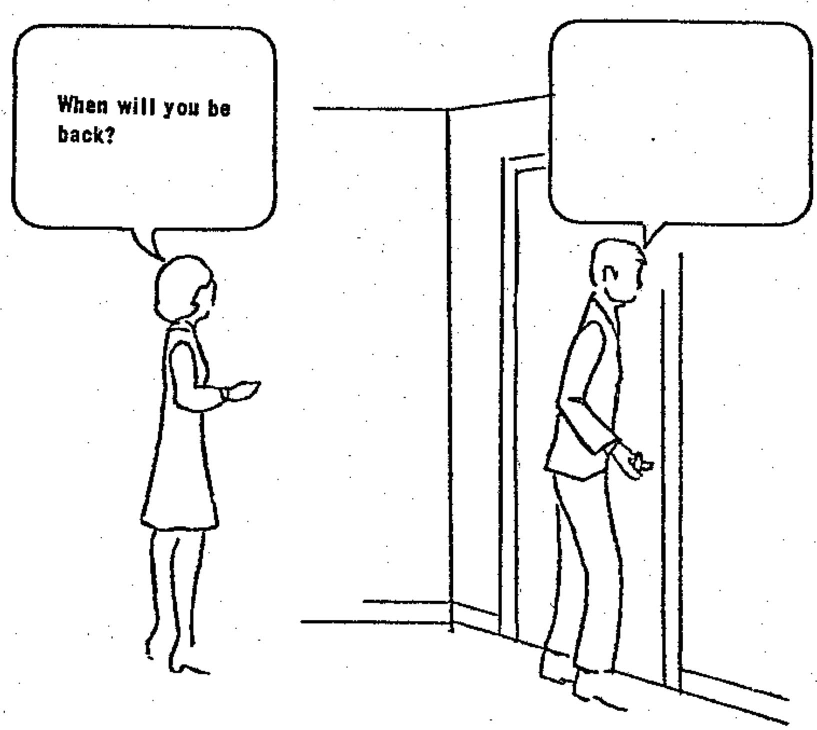
1. Is it too far to walk?
2. They shouldn't let people like that drive busses.
3. Well, I guess we will have to walk.
4. It's too bad. I hope you won't miss something important.
5. I didn't want to go anyway. Let's skip school.

45



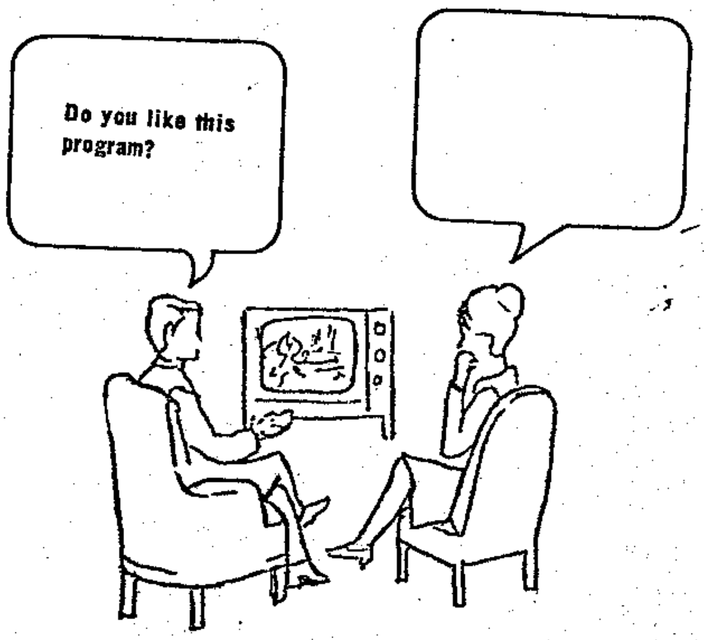
1. Don't worry about it. I'll take you out for supper.
2. That's okay. I can wait.
3. I suppose you were on the telephone all day.
4. When will it be ready?
5. Then I'm going out to eat.

46



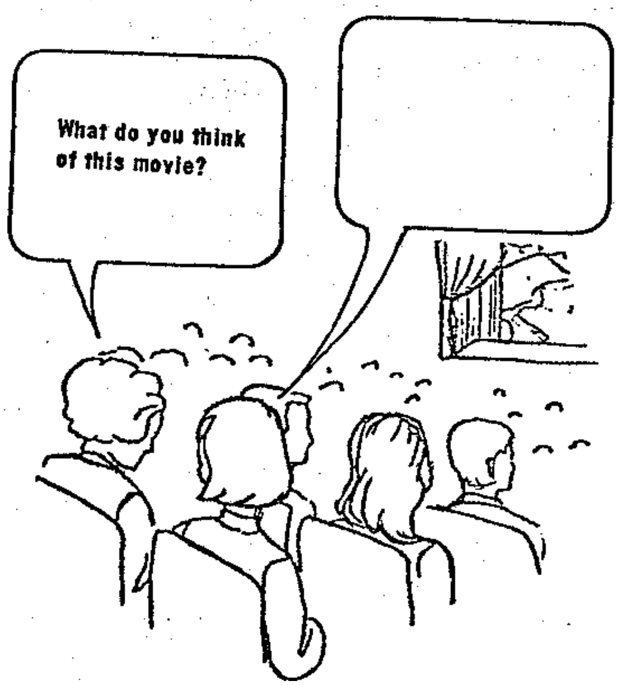
1. I'll come back early like you asked.
2. I'll call you. I don't want you to worry.
3. I'll be back about 6 o'clock.
4. You should know by now when I come back.
5. When I feel like.

47



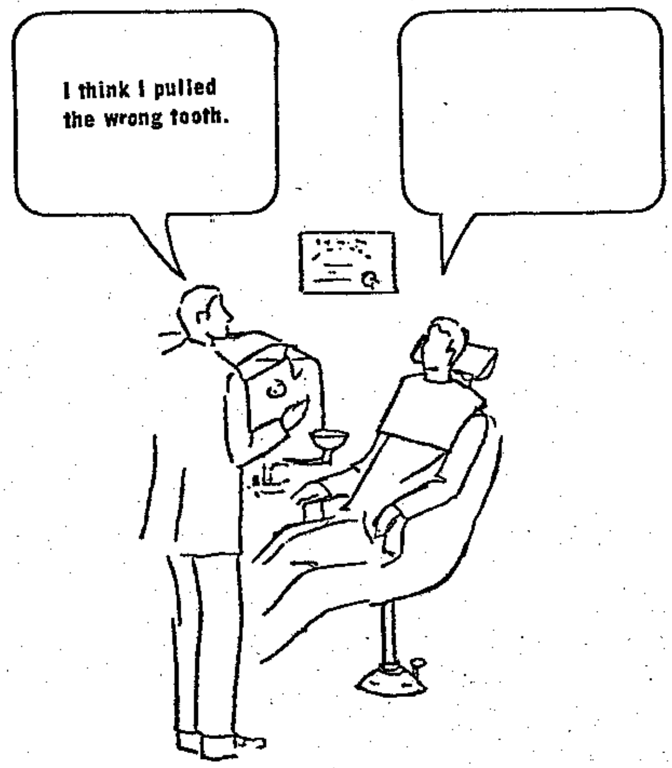
1. It is better than your football games.
2. No, and I'm not going to watch it another minute.
3. No, but I'll watch it if you want to.
4. It is one of my favorites.
5. Yes, I hope you like it too.

48



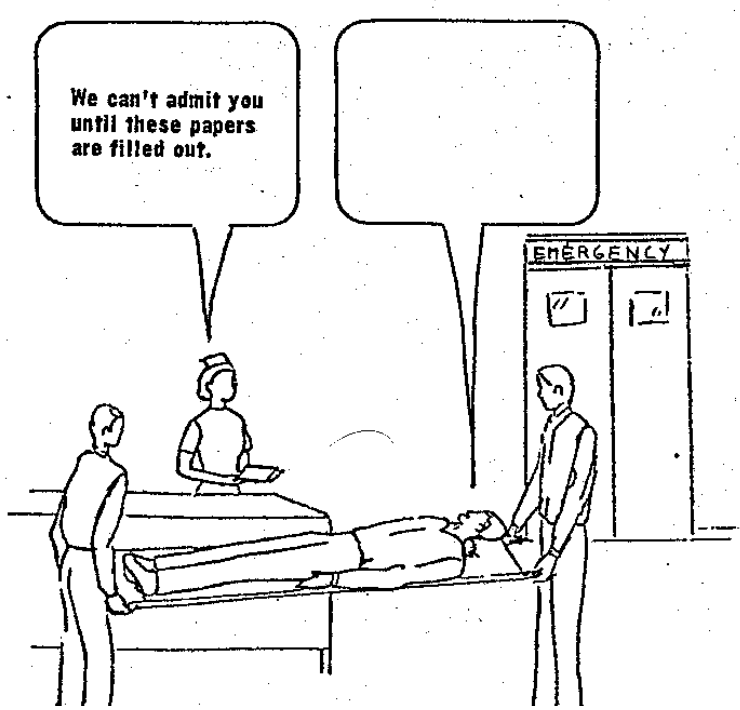
1. What's it to you?
2. I don't like it but I'll stay if you want to.
3. I think it is very well done.
4. It's good. You sure do know how to choose good movies.
5. Be quiet. I'm trying to listen.

49



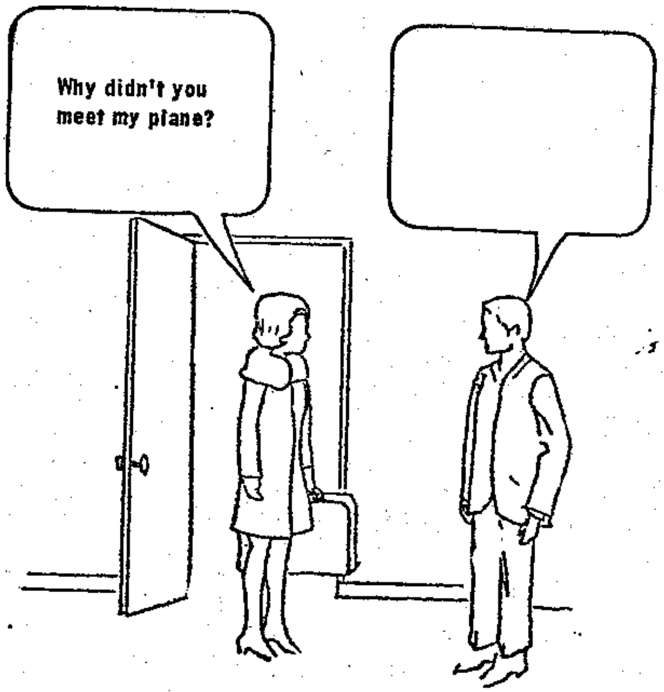
1. What are you going to do about it?
2. Don't worry about it. Everyone makes mistakes.
3. What can be done about it?
4. Oh well, it was probably bad anyway.
5. I'll sue you if you did because you are supposed to know what you are doing.

50



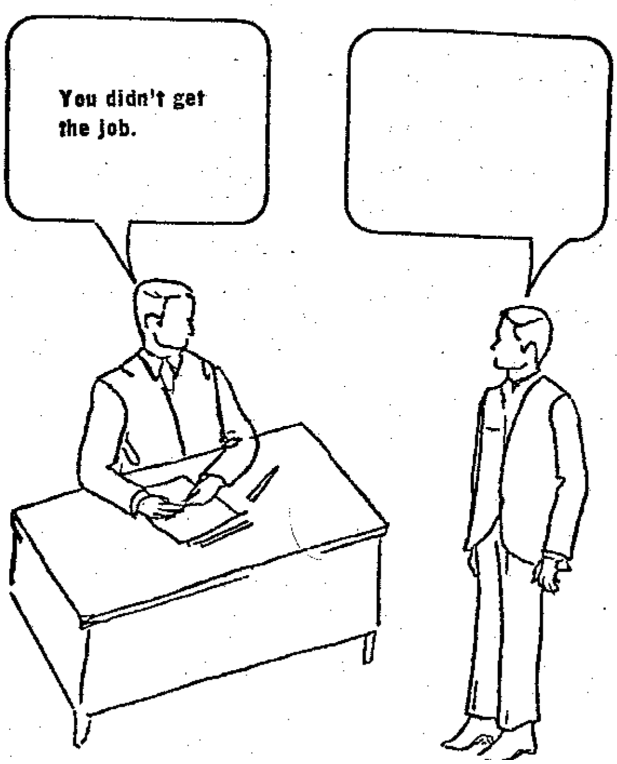
1. It is very good to see that you are handling things properly.
2. Okay, I don't want to break the rules.
3. My wife can give you all the details.
4. You can't make me fill those out.
5. You fill them out and be quick about it.

51



1. You should have telephoned me.
2. I didn't want to so I didn't.
3. What time did your plane arrived?
4. I'm sorry. Next time I'll be there ahead of time.
5. I'm sorry I missed it. May I take your bag?

52



1. I didn't want it anyway.
2. Would you keep my name in your file?
3. Thank you for letting me take so much of your time.
4. Oh well, I guess I'm just not experienced enough.
5. You should have told me sooner that I wasn't qualified.