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Quantitative Analysis of Purposive Systems: Some Spadework at the Foundations of Scientific Psychology

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The revolution in psychology that cybernetics at one time seemed to promise has been delayed by four blunders: (a) dismissal of control theory as a mere machine analogy, (b) failure to describe control phenomena from the behaving system's point of view, (c) applying the general control system model with its signals and functions improperly identified, and (d) focusing on man–machine systems in which the "man" part is conventionally described. A general nonlinear quasi-static analysis of relationships between an organism and its environment shows that the classical stimulus–response, stimulus–organism–response, or antecedent–consequent analyses of behavioral organization are special cases, a far more likely case being a control system type of relationship. Even for intermittent interactions, the control system equations lead to one simple characterization: Control systems control what they sense, opposing disturbances as they accomplish this end. A series of progressively more complex experimental demonstrations of principle illustrates both phenomena and methodology in a control system approach to the quantitative analysis of purposive systems, that is, systems in which the governing principle is *control of input.*

This article concerns four old conceptual errors, two mathematical tools (which in this context may be new), and a series of six quantitative experimental demonstrations of principle that begin with a simple engineering–psychology experiment and go well beyond the boundaries of that subdiscipline. My intent is to take a few steps toward a quantitative science of purposive systems.

Qualitative arguments on the subject of purpose have abounded. Skinner (1972) has expressed one extreme view:

> Science . . . has simply discovered and used subtle forces which, acting upon a mechanism, give it the direction and apparent spontaneity which make it seem alive. (p. 3)

An extreme opposite view is expressed by Maslow (1971):

> Self-actualizing individuals . . . already suitably gratified in their basic needs, are now motivated in other higher ways, to be called "metamotivations." (p. 299)

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In the middle ground are many others who have tried to deal with inner purposes, for example, Kelley (1968), McDougall (1931), Rosenblueth, Wiener, and Bigelow (1968), Tolman (1932), and Von Foerster, White, Peterson, and Russell (1968). I have contributed some arguments as well (Powers, 1973; Powers, Clark, & McFarland, 1960a, 1960b). Obviously, none of these arguments, which are all qualitative, has succeeded in settling the issue of inner purposes.

In the 1940s, many of us thought that the missing quantitative point of view had been discovered. *Cybernetics: Control and Communication in the Animal and the Machine* (Wiener, 1948) seemed to contain the conceptual tools that might at last explain how "mental" causes could enter into "physical" effects. It seemed that a bridge might be built between inner experiences and outer appearances. A cybernetic revolution in psychology seemed just about to start. Now, in the late 1970s, it is still just about to start. Something happened to the original impetus of cybernetics, as a river entering the desert splits into a hundred wandering channels and sinks into the sand. I have some suggestions as to what went wrong.

Four Blunders

It is not so much honest labor on my part that puts my name to this critique as it is a series of blunders (qualitative mistakes) by others who could have done long ago what I am doing now. However unavoidable, these blunders have been directly responsible for the failure of cybernetics and related subjects to provide new directions for psychology.

Machine Analogy Blunder

In 1960, the president of the Society of Engineering Psychologists wrapped up the previous decade of cybernetics as follows:

> The servo-model, for example, about which there was so much written only a decade or two ago, now appears to be headed toward its proper position as a greatly oversimplified inadequate description of certain restricted aspects of man's behavior . . . . Whenever anyone uses the word *model,* I replace it with the word *analogy*. (Chapanis, 1961, p. 126)

This view is still held. There are and have been for some time scientists who think of control system models of behavioral organization as a mere analogy of human behavior to the behavior of a technological invention.

A little digging underneath the engineering models suggests that this opinion is mistaken. Servomechanisms have always been designed to take over a kind of task that had previously been done by human beings and higher animals and by *no other kind of natural system,* that of controlling external variables (bringing them to predetermined states and actively maintaining them in those states against any normal kind of disturbance; Mayr, 1970). It was not until the 1930s, however, that there existed a sufficient variety of sensors or electronic signal-handling devices to permit simulation of the more abstract kinds of human control actions, for example, the adjustment of a meter reading to keep an indicated pH at a predetermined setting. The control-engineers-to-be of the 1930s necessarily had to study what a human controller was doing in order to see just what had to be imitated. The functions of perception, comparison, and action had to be isolated and embodied in an automatic system, a quantitative working model of human organization of a type that psychology and biology had never been able to develop. Thus, the servomechanism has always been only an imitation of the real thing, a living organism, and the engineers who invented it first had to be, however unwittingly, psychologists. The analogy developed from man to machine—not the other way.

Objectification Blunder

The machine analogy blunder set the scene for missing the point of control theory, but the objectification blunder would have been enough by itself. In cybernetics, it arose quite naturally out of the fact that artificial control systems are designed for use by natural ones, that is, human beings.

The designer and user of an artificial control system are understandably interested in the output of the system and effects of that output on the world experienced by the user. Control systems, however, control input, not output. When the input is disturbed, the output varies to oppose incipient changes of the input and thus cancel most of the effect of the disturbance. Thus, the only way to make such systems useful is to be sure that the input to the system depends strictly on the environmental effect that the user wants controlled and to protect the input from all other influences. If that environmental effect is an immediate consequence of output, the output will appear to be controlled as far as the user's purposes are concerned. Indeed, the controlled consequence of the actual output is likely to be called the output.

Natural systems cannot be organized around objective effects of their behavior in an external world; their behavior is not a show put on for the benefit of an observer or to fulfill an observer's purposes. A natural control system can be organized only around the effects that its actions (or independent events) have on its inputs (broadly defined), for its inputs contain all consequences of its actions that can conceivably matter to the control system.

This was Skinner's (1938) momentous dis-

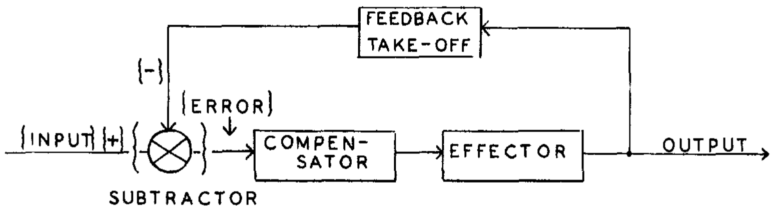

Figure 1. Adaption of Wiener's (1948) control system diagram. (This diagram has misled a generation of life scientists. The "input" is really the reference signal, which in organisms is generated internally. Sensory inputs are actually at the input to the "feedback takeoff." Disturbances of the sensory input are not shown. Adapted with permission from *Cybernetics: Control and Communication in the Animal and the Machine* by Norbert Wiener. Copyright 1948 by M.I.T. Press.)

covery. He concluded that behavior is controlled by its consequences, unfortunately expressing the discovery from the observer's or user's point of view. From the behaving system's point of view, however, Skinner's discovery is better stated in the following way: Behavior exists only to control consequences that affect the organism. From the viewpoint of the behaving system, behavior itself, as output, is of no importance. To deal with behavior under any model strictly in terms of its objective appearance, therefore, is to miss the reason for its existence. Cybernetics and especially engineering psychology simply took over this erroneous point of view from behaviorism. This error is closely related to the next one.

Input Blunder

Wiener himself was accidentally a principal contributor to the input blunder. A diagram from Wiener's (1948) book on cybernetics (see my Figure 1 for an adaption of Wiener's diagram) was taken directly from an engineering and users' viewpoint model. Examining Figure 1, the reader will see that there is an "input" coming in from the left, which joins a feedback arrow at a "subtractor," or more commonly, a "comparator." The "error" signal from the comparator actuates the rest of the system to produce an "output," from which the "feedback" path branches. This basic form has been repeated without change in the literature of psychology, neurology, biology, cybernetics, systems engineering, and engineering psychology from 1948 to the present. It is nearly always interpreted incorrectly.

When a person concerned with sensory processes sees the word *input,* it is natural to translate the term to mean *sensory input* or *stimulus.* But the arrow entering the subtractor is not a sensory input. It is a *reference input,* and the information reaching the subtractor or comparator by that path is by definition and function the *reference signal.* Engineers show reference signals as inputs because artificial control systems are meant for use by human beings, who will operate the system by setting its reference input to indicate the desired value of the controlled variable. In natural control systems, there are no externally manipulable reference inputs. There are only sensory inputs. Reference signals for natural control systems are set by processes inside the organism and are not accessible from the outside. Another name for a natural reference signal is *purpose.* We observe such natural reference signals only indirectly as preferred states of the inputs to the system. Control systems are organized to keep their inputs (represented by the feedback signal) matching the reference signal.

Where, then, are the sensory inputs in Wiener's diagram? They are in the "feedback takeoff" position, or more precisely, they are in the junction where the feedback path leaves the output path. In that same junction are contained all the physical phenomena that lie between motor output and sensory input, which in some cases can include a lot of territory. The arrow labeled "output" and exiting toward the right should really be labeled "irrelevant side effects" because effects of output that do not enter into the operation of this system are of importance only to some

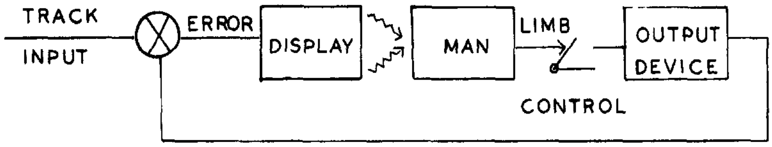

Figure 2. Compensatory tracking. (The "man" is a stimulus–response device embedded in an artificial control system. The influence of Wiener's [1948] diagram is apparent [see the present Figure 1]. Adapted with permission from *Tracking Skill and Manual Control* by E. Poulton. Copyright 1974 by Academic Press.)

external observer or user. Those side effects tell us nothing about the principles of control.

Man–Machine Blunder

If one's primary purpose is to keep pilots from flying airplanes into the ground or to make sure that a gunner hits a target with the shell, that is, if one's purposes concern objectivized side effects of control behavior, the man–machine blunder amounts to nothing worse than a few mislabelings having no practical consequences. If one's interest is in the properties of persons, however, the man–machine blunder pulls a red herring across the path of progress.

Consider Figure 2, adapted from Poulton (1974). The "man" in this experiment is supposed to hold a cursor on the display next to a fiduciary mark; this task is like keeping a ship on a compass course or flying an airplane level by keeping an artificial horizon centered. The immediate task is to maintain a given appearance of the display; a side effect of doing so is to stabilize some objective situation of which the display is a partial representation. The objective situation, of course, is the whole point of the experiment from the experimenter's point of view.

From the subject's point of view, however, the display simply shows a variable picture that the subject can maintain in any stable condition desired. The subject could keep the cursor a fixed distance off the fiduciary mark, as a pilot could keep the artificial horizon above the center mark while deliberately losing altitude, or as a navigator–helmsman could keep the compass reading several degrees east of the intended course in order to compensate for a remembered westward deviation of magnetic north from true north.

The so-called "error" in Figure 2 is not an error at all; the error corresponds to a sensory input, both for the subject and for the experimenter. The crossed circle is not a comparator, but only a place where external disturbances join feedback effects in determining the state of the display. Wiener's diagrams did not show disturbances.

Only the subject has a means of directly affecting the state of the display; hence, the display will be made to match the subject's inner reference. If doing this causes the experimenter to see an error (Figure 2 shows the experimenter's point of view), the only corrective action the experimenter can take is to halt the experiment and persuade the subject to reset his inner reference signal to produce a result the experimenter experiences as zero error.

That, of course, is what is done. By demonstration and instruction, the subject is shown where to set his internal reference; if the subject complies, the experiment proceeds. The analysis of the data can then be done under the assumption that there is no offset in the "man" box. Thus objectifying the error assures that the experiment will not reveal one of the most important properties of the subject: the ability to manipulate an inner reference signal. As this situation is usually analyzed, the man's purposive properties drop from view, and those of the experimenter are quietly incorporated into the so-called "objective" analysis.

From the General to the Specific

The preceding discussion suggests that the failure of control theory to create a cybernetic revolution in psychology may not have been the fault of control theory. I hope my implied criticisms have stayed on target because there is no reason to belittle what cyberneticists have done or what engineering psychologists have discovered. The blunders I have described are principally blunders of omission and misinterpretation that have unnecessarily but unavoidably limited the scope of these endeavors. I shall commit blunders of my own just like these, as will we all. That is the penalty for trying something new.

In trying to develop control theory as a tool for experimental psychology, I think it is important to avoid assuming that any example of behavior involves a control organization. I have been critical of some psychologists for adopting a language that periodically asserts a model by calling every action a "response," but I succumb to the same kind of temptation myself when trying to convey my own point of view. A basic analysis cannot be very convincing if its conclusions are plugged in where the premises are supposed to go, so in the following section, the treatment will begin in as general a form as possible.

Let us assume little more than the early behaviorists did, and in some respects, let us assume a great deal less. The organism will be treated as nothing more than a connection between one set of physical quantities in the environment (input quantities) and another set of physical quantities in the environment (output quantities). By leaving the form of the organism function general, however, we will allow for possibilities that were tacitly ruled out at the turn of the century, the most important one being the possibility of a secularly adjustable constant term in the system function. That term will ultimately turn into the observable evidence of an inner purpose, although I will not pursue that point vigorously here.

This approach will explicitly recognize the fact that the inputs to an organism are affected not only by extraneous events but possibly by the organism's own actions. By leaving the development general, we will be able to deal deductively with feedback effects, not asserting them but simply stating the observable conditions under which they necessarily appear and those under which they can be ignored. Thus, the classical mechanistic cause–effect model will become a subset of the present analysis.

Let us now turn to mathematical tools, beginning with an approach that is neither as detailed as possible nor as general as possible but that is, to my taste, just right (naturally).

The Quasi-static Approach

A quasi-static approach is one in which physical variables, although known to be subject to dynamic constraints, are treated as algebraic variables. In the physical sciences, this is a commonplace procedure. For example, the motions of the free ends of a lever are treated as if the motions of one end were literally simultaneous with the motions of the other end; inertia and transverse waves propagating along the lever are ignored. If a real lever is moved too rapidly, it will bounce off its fulcrum; one does not expect a quasi-static analysis to hold for such extreme cases.

The validity of the quasi-static approach as well as its usefulness depend on the frequency domain of interest. The designer of a man–machine system focuses on the high-frequency limits of performance because his task is not to understand the man but to get the most out of the machine for some extraneous purpose. This is the origin of the transfer function approach, and the reason why the engineering models can get away with treating the man in the system as an input–output box.

I am interested in the frequency domain that lies between a pure steady state and the "corner frequency," where the quasi-static analysis begins to break down. Thus, the analysis here does not encroach on the territory of engineering psychology. In the present analysis, there would be no point in carrying the transient terms of interest in engineering psychology because they go to zero before they become important. There would be a positive disadvantage in using mathematical forms that map the space being investigated into an intuitively unrecognizable space with nonphysical variables in it ("cisoidal oscillations" or imaginary quantities found in Laplace transform theory and commonly applied to control systems; see Starkey, 1955, p. 31). The following analysis, while of little use for measuring transfer functions in the normal way, is suited to the elucidation of the structure of behavioral organization.

A Quasi-static Analysis

Consider a behaving system ("system" for short) in relationship to an environment. The system is the simplest possible: It has one sensory input affected by an input quantity, q_i, and one output that affects an output quantity, q_o. Both q_i and q_o are ordinary physical quantities in the environment or else are regular functions of measurable physical quantities.

In general, a change at the input to the system will result in a change at the output because of intervening system characteristics. The output quantity will be related to many other external quantities, but the only one of interest here is q_i, the input quantity. The input quantity will also be subject to disturbances from variables that change or remain constant independently of the output of the system.

The assumption of dynamic stability is made: After any transient disturbance, the system–environment relationship will come to a steady-state equilibrium quickly enough to permit ignoring transient terms in the differential equations that actually describe the relationship. This assumption implies the use of an averaging time or a minimum time resolution appropriate to each individual system.

It should not be thought that this assumption limits us to a static case. In the equation $F = MA$, or force equals mass times acceleration, the algebraic variable A is really the second derivative of position with respect to time. Nevertheless, there are many useful and accurate applications of this algebraic formula in dynamic situations. In a great variety of situations, time-dependent variables can be dealt with quasi-statistically simply by a proper definition of the variables. All that is lost is the ability to predict behavior near the dynamic limits of performance in terms of the chosen variables. The system equation is

$$q_o = f(q_i),\ f \text{ being a general algebraic function.} \qquad (1)$$

(Small letters will be used for functions and capital letters for multipliers of parenthesized expressions when ambiguity is possible.)

The environment equation contains two terms representing linearly superposed contributions from two sources, which together determine completely the state of the input quantity. One contribution comes from the output of the system via q_o. The magnitude of q_o contributes an amount $g(q_o)$, where g is a general algebraic function describing the physical connection from q_o to q_i: This is the feedback path, which is missing when $g(q_o)$ is identically zero.

All other possible influences on the input quantity that are independent of q_o are summed up as an equivalent disturbing quantity, q_d, contributing to the state of q_i through an appropriately defined physical link symbolized as the function h; the magnitude of the contribution from disturbing quantities is thus $h(q_d)$. This provides the following environment equation (see Figure 3):

$$q_i = g(q_o) + h(q_d). \qquad (2)$$

The assumption of dynamic stability permits treating the system and environment equations as a simultaneous pair. To find a general simultaneous solution valid for all quasi-static cases in which physical continuity exists, we shall rearrange Equations 1 and 2 into equally general forms that are more manipulable. First, a Taylor series expansion of $f(q_i)$ is performed around a special (and as yet undefined) value, q_i^*, and an expansion of $g(q_o)$ is done about the corresponding special value q_o^*. For $f(q_i)$, the factor $(q_i - q_i^*)$ is factored out of the variable terms, leaving the following quotient polynomial:

$$q_o = f(q_i^*) + (q_i - q_i^*)\,[A + B(q_i - q_i^*) + C(q_i - q_i^*)^2 \ldots].$$

A, B, C, and so on are the Taylor coefficients. The quotient polynomial is symbolized as U to yield the following working system equation:

$$q_o = f(q_i^*) + U(q_i - q_i^*). \qquad (3)$$

In a parallel manner, with the quotient polynomial symbolized as V, $g(q_o)$ is represented as $g(q_o^*) + V(q_o - q_o^*)$ to yield the

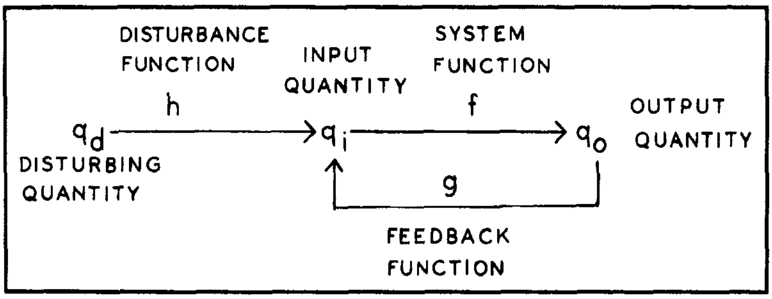

Figure 3. Relationships among variables and functions in the quasi-static analysis. (The topological similarity of Wiener's [1948] diagram, adapted in the present Figure 1, is of no significance because these variables and functions all pertain to observables outside the organism. This is not a model of the organism; it is a model of the organism's relationships to the external world.)

working environment equation of

$$q_i = g(q_o^*) + V(q_o - q_o^*) + h(q_d). \quad (4)$$

Let the special value of q_i, or q_i^*, be defined as the value of q_i when there is no net disturbance: $h(q_d) = 0$. Then $q_i^* = g(q_o^*)$ and $q_o^* = f(q_i^*)$. Substitutions into Equations 3 and 4 then yield

$$q_o - q_o^* = U(q_i - q_i^*) \quad (5)$$

and

$$q_i - q_i^* = V(q_o - q_o^*) + h(q_d). \quad (6)$$

Substitution of Equation 6 into Equation 5 produces, after some manipulations twice involving the equivalence $V(q_o - q_o^*) = g(q_o) - g(q_o^*)$, Equation 7:

$$g(q_o) = q_i^* + \left(\frac{UV}{1 - UV}\right)h(q_d), \quad \text{where} \quad UV \neq 1. \quad (7)$$

Substituting from Equation 5 into Equation 6 directly yields Equation 8:

$$q_i = q_i^* + h(q_d)/(1 - UV), \quad \text{where } UV \neq 1. \quad (8)$$

The dimensions of U are change of output per unit change of input, and the dimensions of V are change of input per unit change of output. Thus, the product UV is a dimensionless (and variable) number. It is customarily called the *loop gain* in morphologically similar equations of control theory.

So far these equations remain completely general, applying to any system–environment relationship of the basic form assumed, when the assumption of dynamic stability is observed to hold true. No model of the internal organization of the behaving system has been assumed, nor has it been assumed that we are dealing with a control system or even a feedback system. The only limits set on nonlinearity of the functions are practical ones: Systems that are radically nonlinear are not likely to meet the assumption of dynamic stability. These prove to be quite permissive limits.

Classifying System–Environment Relationships

The behavior of a system as defined here can be classified according to the observed magnitude and sign of the loop gain, UV. A severely nonlinear system can conceivably pass from one class to another during behavior.

Type Z: Zero Loop Gain

If the product UV is zero because the function f is zero, there is no behaving system. If it is zero because the function g is zero, there is no feedback and the simultaneous solution of the equations becomes (from Equations 1 and 2)

$$q_o = f(q_i) = f[h(q_d)].$$

This is the *open-loop* case and corresponds to the classical cause–effect model of behavior. If q_i is considered a proximal stimulus (located at the sensory interface or even at some stage of perceptual processing inside the system) and q_d a distal stimulus, then the output or behavior is mediated by the organism according to the form of the function f, and the proximal stimulus is the immediate cause of behavior. A stimulus object or event operates from its distal position as q_d, affecting the proximal stimulus q_i through intervening physical laws described by the function h. Thus, a simple lineal causal chain links the distal stimulus to the behavior.[1]

I shall say *Z system* to mean a behaving system in this Type Z relationship to its environment. In order to show that a given organism should be modeled as a Z system, it is necessary to establish that the organism's own behavior has no effect on the proximal stimuli in the supposed causal chain. I believe that this condition is, in any normal circumstance, impossible to meet. I will show later that even separating stimulus and response in time will not make the Z-system model acceptable.

Type P: Positive Loop Gain

If UV is positive and not zero, there is a Type P, or positive feedback, relationship between system and environment. The behaving system is then acting as a *P system.* This type of relationship is dynamically stable only for $UV < 1$. A dynamic analysis is needed to show what happens for $UV \geq 1$; the algebraic equations give spurious answers. The P system goes unconditionally into self-sustained oscillations that either continue at a constant amplitude or increase exponentially or simply head for positive or negative infinite values of its variables. Whichever happens, the quasi-static analysis breaks down, as does the behavior of the system, since this is not generally considered normal behavior. A Type P relationship is dynamically stable only for $0 < UV < 1$.

There have been qualitative assertions in the literature that positive feedback may be beneficial because it "enhances" or "amplifies" responses. Such assertions are uninformed. Positive feedback does amplify the response to a disturbance because in a Type P relationship, behavior *aids* the effects of the disturbance on the input quantity. Equation 7 can be used to calculate the amplifying effects of various amounts of positive feedback, with the amplification factor being $UV/(1 - UV)$. The following list is an example of these calculations:

UV	Amplification factor
.5	1.0
.6	1.5
.7	$2.\bar{3}$
.8	4.0
.9	9.0
.99	99.0
$\geq 1.\bar{0}$	unstable

In a nonlinear system, UV varies with the magnitude of disturbance; furthermore, natural systems have muscles that fatigue and interact with environments having variable properties. These facts are incompatible with the narrow range of values of UV (shown above), in which any useful amount of amplification is obtained from positive feedback. The relationship would always be on the brink of instability under the best of circumstances. We may expect natural P systems to be rare.

Type N: Negative Loop Gain

If UV is negative and not zero there is a Type N, or negative feedback, relationship between system and environment. The system is an *N system.* UV may have any negative value. In N systems, preservation of dynamic stability requires a trade-off between the magnitude of UV and the speed of response of the system. Servo-engineers would recognize the great advantage we have here over the person who has to design such a system: The designer has to tailor the dynamic characteristics to make the system–environment relationship stable; we only have to observe that it actually is stable. The equations we are using would be of no help to a designer of control systems.

It is difficult to find an example of behavior in which the feedback connection g is

[1] *Lineal* means occurring along a line or in simple sequence, as in lineal feet. *Linear* means described by a first-degree equation: For example, the equation $y = 3x$ expresses a linear relationship between x and y, while $y = 3x + 1/x$ expresses a nonlinear relationship.

missing; feedback is clearly present in most circumstances. Moreover, it is generally found that organisms are sensitive to small changes of stimuli and that feedback effects are pronounced, so the magnitude of UV must be assumed in general to be large. Since we do not commonly observe dynamic instability, it follows that the sign of U must be opposite to that of V, that is, that the feedback is negative and the system an N system under most circumstances. Detailed investigation of individual cases, of course, will settle the question. I hope, however, that it can be seen that the Type N relationship is an important one. We shall examine its properties.

Properties of the Type N relationship. On the right side of Equation 7 is the expression $UV/(1 - UV)$, a form familiar in every mathematical approach to closed-loop analysis. With UV being dimensionless and negative for N systems, this expression is a dimensionless negative number between 0 and -1. Furthermore, the larger the minimum value of $-UV$ becomes, the more nearly $UV/(1 - UV)$ approaches the limiting value -1. When this limiting value is closely approached, we can call the system an *ideal N system.*

In the experiments to be described, the typical minimum value of UV estimated from the data was -30. Thus, only a 3% error is entailed in saying that subjects behaved as ideal N systems, in which $(-UV)$ is extremely large.

For an ideal N system, Equations 7 and 8 reduce to especially simple forms:

$$g(q_o) = q_i^* - h(q_d) \qquad (7a)$$

and

$$q_i = q_i^*. \qquad (8a)$$

From these equations can be drawn two basic statements that characterize a wide variety of N systems but more accurately for those that approach the ideal N system. Equation 7a is easier to translate if we remember that $q_i^* = g(q_o^*)$. The term $g(q_o)$ represents the effect of the output on the input quantity, $h(q_d)$ represents the effect of the disturbance on the input quantity, and q_o^* is the value of the output when there is no disturbance acting. It follows that the change in the output quantity away from the no-disturbance case is just what is required to produce effects on the input quantity that cancel the effects of the disturbance. Equation 8a expresses the consequence of this cancellation: The input quantity remains at its undisturbed value, q_i^*. Thus, the actions of an N system, mediated by the feedback path, stabilize its input quantity against the effects that disturbances otherwise would have. An ideal N system does this perfectly.

It will be seen that the widespread notion that negative feedback systems control their outputs is a misconception. In an artificial control system designed to produce outputs of interest to a user, the feedback function g is selected to make sure that q_i is precisely related to some objective consequence of q_o, so that controlling q_i will indeed result in controlling the objective consequence of q_o; however, such systems are built to protect themselves from all disturbances that might affect q_i directly. The erroneous transfer of an engineering model directly into a behavioral model was the cause of the misconception. The engineering model would show a reference input to the system, the effect of which would be to adjust the setting of q_i^* and also to indirectly affect the objective consequence. As mentioned, no such input from the outside exists in natural N systems (in none of those, at any rate, that I have investigated).

A behavioral illusion. Solving Equation 7a for q_o produces

$$q_o = g^{-1}[q_i^* - h(q_d)].$$

Compare this form with the equation for a Z system:

$$q_o = f[h(q_d)].$$

The difference in sign is a matter of choice of coordinates, and the constant q_i^* can be used as the zero of the measurement scale, so the forms are essentially the same. The primary difference is that the organism function f in the Z-system equation is replaced by the inverse of the feedback function g^{-1} in the N-system equation.

This comparison reveals a behavioral illusion of such significance that one hesitates to believe it could exist. If one varies a distal stimulus q_d and observes that a measure of behavior q_o shows a strong regular dependence on q_d, there is certainly a temptation to assume that the form of the dependence reveals something about the organism. Yet, the comparison we have just seen indicates that the form of the dependence may reflect only properties of the local environment. The nightmare of any experimenter is to realize too late that his results were forced by his experimental design and do not actually pertain to behavior. This nightmare has a good chance of becoming a reality for a number of behavioral scientists. An example may be in order.

Consider a bird with eyes that are fixed in its head. If some interesting object, say, a bug, is moved across the line of sight, the bird's head will most likely turn to follow it. The Z-system or open-loop explanation would run about like this: The bug's position, the distal stimulus, is translated by optical effects into a proximal stimulus on the retina, exciting sensory nerves and causing the nervous system to operate the muscles that turn the head. This causal chain is so precisely calibrated and its form so linear that the movement of the head exactly compensates for the movement of the bug. The image thus stays centered on the retina.

There is a reason why this kind of explanation skips so rapidly across the proximal stimulus. If the head tracks the bug perfectly, the image of the bug will remain stationary on the retina, as indeed it very nearly does. But if the image remains stationary or wanders unsystematically about one point, the causal chain cannot be followed through. The open-loop explanation contradicts itself.

If the angle of the head is q_o and the visual angle of the bug is q_d, q_o has precisely as much effect as q_d has on q_i, the position of the retinal image. By choosing units properly, therefore, we can say that both g and h are unity multipliers of opposite sign. The two functions reflect the laws of geometric optics and, hence, are exquisitely precise and linear.

Equation 7a predicts that for an ideal N system, the output will vary as the inverse g function of the effect of the disturbance. Thus, the relationship between q_d and q_o will be as precise and linear as the laws of geometric optics. The organism function f, on the other hand, may be both nonlinear and variable over time. As long as the polynomial U remains large enough, the apparent behavioral law will be unaffected.

Thus, in the relationship between bug movement and head turning, we are not seeing the function f that describes the bird; instead, we are seeing the function g that describes the physics of the feedback effects. This property of N systems is well known to control engineers and to those who work with analog computers. It is time behavioral scientists became aware of it, whatever the consequences.

Operant Conditioning

The quasi-static analysis works quite well in at least one kind of operant-conditioning experiment: the fixed-ratio experiment, in which an animal provides food for itself on a schedule that delivers one pellet of food for each n presses of a lever.

The function g becomes just $1/n$, and there is no disturbance $[h(q_d) = 0]$.[2] The environment equation reduces to

$$q_i = q_o/n. \tag{9}$$

The average rate of reinforcement is treated as being the input quantity. The equations for an ideal control system predict that $q_i = q_i^*$, which is to say that the organism will keep the average rate of reinforcement at a level q_i^* that is determined by a property of the organism. The average rate of bar pressing, using Equation 7a, will be $q_o = nq_i^*$.

From Equation 7a, we can predict what will happen if the schedule is changed from n_1 to n_2. The corresponding rates of bar pressing, q_{o1} and q_{o2}, will be related by

$$q_{o1}/q_{o2} = n_1/n_2. \tag{10}$$

The more presses are required to deliver one pellet, the more rapidly, in direct proportion, will the animal work the lever. This is a well-known empirical observation, found while "shaping" behavior to very high response rates.

A disturbance could be introduced by adding food pellets to the dish where pellets are

[2] Excessive efforts, on extreme schedules, would introduce a disturbance.

delivered by the lever pressing at a rate q_d (the function h is then 1). The environment equation would then be

$$q_i = q_o/n + q_d. \qquad (11)$$

From the solution for an ideal N system, we find

$$q_o = n(q_i^* - q_d). \qquad (12)$$

If q_i^* is the observed rate of reinforcement in the absence of the disturbance, the rate of lever pressing in the presence of arbitrarily added food can be predicted. The average pressing rate will drop as the rate of adding food rises. When food is added arbitrarily at a rate just equal to q_i^*, lever pressing will just cease. This prediction is in accord with scientific observation (Teitelbaum, 1966) and with the qualitative empirical generalization that noncontingent reinforcement reduces behavior.[8]

It is evident that in order to predict quantitatively the results of this kind of operant-conditioning experiment, all one needs to assume about the organism is that it is an ideal N system. The value of q_i^* can be found with one observation, and a whole family of relationships can be predicted thereafter. Conversely, the information obtained about the organism in such an experiment is only that it does act as an ideal N system controlling the rate of reinforcement. This analysis, while not dealing with learning, shows that changes of behavior do not necessarily imply any change of behavioral organization.

Let us now turn to a second quantitative method, which will be discussed more briefly but needs to be discussed because it deals with time delays, which the quasi-static approach cannot handle.

A Time–State Analysis with Dynamic Constraints

One persistent and incorrect approach to feedback phenomena is to treat an organism as a Z system, with any feedback effects being treated as if they occurred separately, after one response and before the next, thus apparently permitting the system itself to be dealt with in open-loop fashion. Qualitatively, this seems to work; but, as in every open-loop analysis, the approach fails quantitatively. The knowledge-of-results or stimulus–response–stimulus–response . . . analysis seems to succeed only because of the limitations of verbal or qualitative reasoning.

I shall use a linear model here, so I can focus on the main point without excessive complication. Let us alternate between the organism and the environment, first calculating the magnitude of the output quantity that results from the current magnitude of input and then calculating the next value of the input from the value of the output and the magnitude of the (constant)disturbance. This procedure leads to two modified equations. The system equation will be

$$q_{o(t+1)} = F(q_i - q_i^*)_t, \qquad (13)$$

and the environment equation will be

$$q_{i(t)} = Gq_{o(t)} + Hq_d. \qquad (14)$$

The functions f, g, and h have been translated into linear multipliers F, G, and H; and a time index, t, has been introduced. The loop gain is now the product FG, which corresponds to UV previously.

To skip a useless analysis, I will report that this set of equations converges to a steady state with FG in the range between $+1$ and -1 but not at or outside those limits. With the loop gain FG limited to $FG > -1$, the behaving system certainly cannot act like an ideal N system. The permissible amount of feedback is so small that there would be little behavioral effect from having any at all (except possible proneness to instability).

The difficulty here is that a sequential-state analysis of this kind introduces time without taking into account phenomena that depend on time. In the design of logic circuits, this can perhaps be done successfully, although a tight design has to recognize the fact that so-called "binary variables" in a logic network are really continuous physical quantities that, like any quantities in the macroscopic world, take time to change from one state to another. Ones and zeros exist only in abstract machines.

Without getting into a full dynamic analysis, we can introduce a dynamic constraint on this system by allowing the output to

[8] This is an excellent experimental method for measuring q_i^* in a natural situation.

change only a fraction of the way from its current value of $q_{o(t)}$ toward the next computed value of $F(q_i - q_i^*)_{(t)}$ during the time between one value of t and the next. Letting K, a number between 0 and 1, be this fraction, let us introduce a modified system equation with this dynamic constraint:

$$q_{o(t+1)} = q_{o(t)} + K[F(q_{i(t)} - q_i^*) - q_{o(t)}]. \quad (15)$$

Substituting Equation 14 into Equation 15 now yields

$$q_{o(t+1)} = q_{o(t)} + K[FGq_{o(t)} + FHq_d - Fq_i^* - q_{o(t)}],$$

or

$$q_{o(t+1)} = q_{o(t)}(1 + KFG - K) + KF(Hq_d - q_i^*). \quad (16)$$

A steady state for repeated calculations with Equation 16 will be reached in one jump if $(1 + KFG - K) = 0$, implying an optimum value for K of

$$K_{opt} = 1/(1 - FG). \quad (17)$$

Setting $q_{o(t+2)} = q_{o(t)}$ leads to the value of K at which the system just goes into endless oscillation, that is, the critical value or upper limit of K:

$$K_{crit} = 2/(1 - FG) = 2K_{opt}. \quad (18)$$

If $K_{opt} < K < K_{crit}$, the successive iterations of Equation 16 oscillate above and below the steady-state solution, converging more and more rapidly as K approaches K_{opt}. For $0 < K < K_{opt}$, the successive iterations approach the same steady state but in an exponential monotonic way. In any case, the steady state (ss) is that found by substituting K_{opt} into Equation 16, with the result

$$q_{o(ss)} = \left(\frac{FG}{1 - FG}\right)\left(\frac{Hq_d}{G} - \frac{q_i^*}{G}\right). \quad (19)$$

For $FG \ll -1$ (an ideal N system), the expression $FG/(1 - FG)$ can be replaced by -1 to yield

$$Gq_{o(ss)} = q_i^* - Hq_d. \quad (20)$$

Comparing this with Equation 7a,

$$g(q_o) = q_i^* - h(q_d),$$

one can see that the linear sequential-state analysis with a dynamic constraint provides the same final picture of behavior that the quasi-static analysis provides. Treating behavior as a succession of instantaneous events propagating around a closed loop will not yield a correct analysis, no matter how tiny the steps are made, unless this dynamic constraint is properly introduced. With the dynamic constraint, the discrete analysis shows that behavior follows the same laws of negative feedback whether the feedback effects are instantaneous or delayed. This consideration has not, to my knowledge, been taken into account in other discrete analyses of behavior.

I have found this iterative approach useful in constructing computer simulations; even for highly nonlinear systems, it is usually possible to find a value of K that will stabilize the model. The behavior is essentially that of a system with a first-order lag.

Experimental Demonstrations of Principle

Let us now look at six experiments that bring out fundamental aspects of this approach. They are not thought experiments, although I will describe them only in general terms; they were done with an on-line computer system using real subjects. The aim of the experiments was not to begin serious explorations of human nature using these organizing principles; that task lies in the future (and I hope I will not be the only one involved in it). The purpose of this effort has been to select from among dozens of experiments tried over the past 3 years a few that are easily replicated by many means that produce reliable results that can be explained only by the version of control theory used here and that always give accurate quantitative results, as good as those obtained in the laboratory demonstrations in introductory physics courses. Of course, the point of these experiments will be lost if nobody else tries them.

There is a way to tell when one has thoroughly understood each experiment and has discarded all inappropriate points of view. This is to persist until it is seen exactly why each quantitative result occurs as it does.

When one realizes that no other outcome is possible for an ideal N system, one fully understands the experiment and also how an ideal N system works. To communicate that kind of understanding is what I hope for here.

General Experimental Method

A practiced subject sits facing a cathode-ray tube (CRT) display while holding the handle of a control stick that is pivoted near the subject's elbow. The angle of the control stick above the horizontal is considered the positive direction of behavior, below being the negative, and a digitized version of that measure in the computer is defined as the output quantity q_o.

On the screen is a short horizontal bar of light that can move up and down only over a grid of dots that remains stationary, providing a reference background. The position of the bar, or cursor, above or below center is taken as the input quantity, its measure being the digital number in the computer corresponding to displayed position q_i. This remotely defined q_i is valid because there are no disturbances intervening between subject and display that could alter the perceived figure–ground pattern.

Inside the computer is a random-number routine that repeats only after 37,000 hours of running time. Another routine smooths this random number, limiting its band width to about .2 Hz. The resulting number is the disturbing quantity q_d. The subject has no way to sense the magnitude of q_d directly.

The position of the cursor is completely determined at every instant (that is, 60 times per sec) by the sum of q_o and q_d. When all quantities are expressed in terms of equivalent units on the screen, the environment equation corresponding to Equation 1 is

$$q_i = q_o + q_d. \qquad (21)$$

The system equation is just Equation 1: $q_o = f(q_i)$, where f is some general quasi-static algebraic function. The handle position is thus taken to depend in some way on the sensed position of the cursor.

A typical run begins with q_d forced to zero. During this time, the value of q_i is determined. By definition, this value is q_i^*. It is always measured, even though the instructions may appear to predetermine it; subjects do not always set q_i in the way the experimenter had in mind. A typical run lasts 60 sec after the random-number program is allowed to continue. The random-number generator runs continuously, but for the first part of each experiment, zero is substituted for the output of the smoothing routine. So far no two experimental runs have employed the same pattern of disturbances. If this seems like excessive zeal to attain randomness, it is done because a critic once suggested, apparently seriously, that the sine-wave disturbances I used at first were being memorized by the subject, even though there was no way for the subject to detect errors in phase or amplitude between the subject's actions and the changes in the disturbance and no way to sense the disturbance.

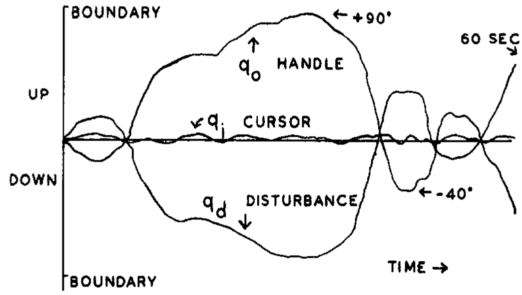

Figure 4. Experiment 1 results drawn from the cathode-ray tube (CRT) display of data. (The "cursor" trace represents the up–down position fluctuations that the subject sees on the CRT screen. The "disturbance" trace represents the invisible random quantity that is added to a representation of handle position ["handle" trace] to determine the position of the cursor.)

Experiment 1: Basic Relationships

The subject is requested to hold the cursor even with the center row of background dots (a standard compensatory tracking experiment). The value of q_i^* is determined as above, and the run commences. From Equations 7a and 8a, which presume that the subject is an ideal N system, it is predicted that $q_i = q_i^*$ and $q_o = q_i^* - q_d$. Here, q_i^* should be zero and very nearly is.

Figure 4 is a drawing of a typical result from a plot on the CRT screen. Any practiced subject will produce this kind of pattern.

The root mean square (RMS) variations of q_i about q_i^* ($= 0$ here) are about plus or minus 2% of full scale. Thus, q_o is, within the same tolerance, a mirror image of the disturbance q_d.

A minimum value of U can be estimated from a simulation that best fits the data. For most practiced subjects, it is at least -30 and may be much larger. The data suggest a first-order lag system (output proportional to integral of $q_i - q_i^*$), but no attempt was made to determine a valid transfer function. The assumption of stability is clearly met. There is little doubt that we are seeing a nearly ideal N system.

The best way to gain an intuitive understanding of Figure 4 is to start with the ob-

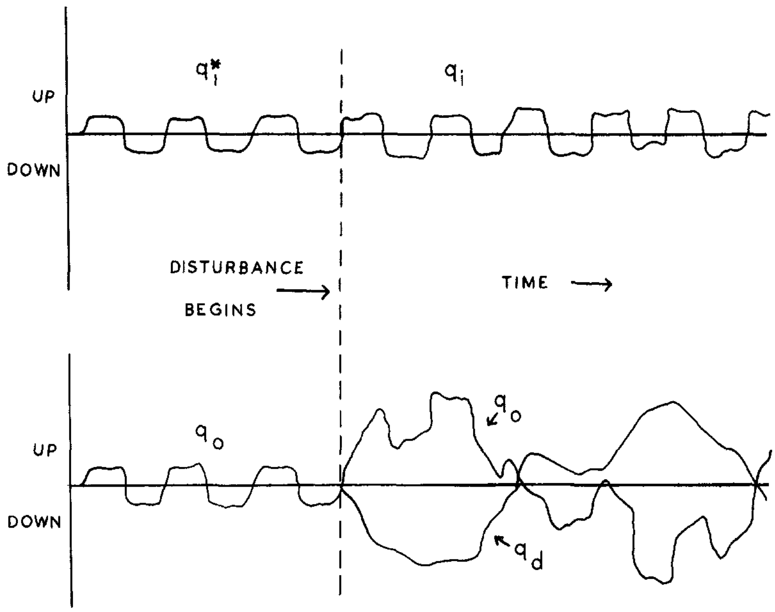

Figure 5. Experiment 3 results drawn from the cathode-ray tube (CRT) display of the data. (The upper trace shows the behavior of the cursor [q_i] on the CRT screen without [left] and with [right] the disturbance acting. The lower trace shows the handle position [q_o] with no disturbance acting [left] and the handle position [q_o] and disturbance magnitude [q_d] when disturbance begins changing [right]. The output, not the input, directly reflects the disturbance. The duration of the run was about 1 minute.)

served fact that the input quantity remains essentially at the value q_i*. It follows that the handle must always be in the position that balances out the effect of the disturbance. We are not modeling the interior of the subject, so we need not worry about how this effect is created. It is a fact to be accepted. From the fact that the input is stabilized, the other relationships follow.

Experiment 2: Unspecified q_i*

The subject is now asked to hold the cursor in "some other position," as accurately as possible. With $q_d = 0$, q_i* is measured, and the run commences. The results are the same as before, with a nonzero value of q_i*. This variation on Experiment 1 shows that the subject, not the apparatus or the experimenter, determines a specific quantitative setting of q_i*.

Experiment 3: Change of Variable

The subject is asked to make the cursor move in any slow rhythmic pattern, the same pattern throughout the run. The subject indicates when the pattern on the screen (with $q_d = 0$) is the one to be maintained. The run commences. The initial pattern is taken to be q_i*; there are many means for characterizing a temporal pattern quasi-statistically, such as phase, amplitude, or frequency measures (one or more of which might prove to be controlled or uncontrolled). I used a much more subjective method, adequate for present purposes although not for serious work: eyeballing the data.

A typical result is shown in Figure 5. A separate plot is given for q_i to avoid confusing the curves. Without any disturbance, the measure of handle behavior is the same as the measure of the input quantity. Regularities in the cursor behavior appear to be just reflections of regularities in the handle behavior. When the disturbance is applied to the cursor, however, it is the handle behavior, not the cursor behavior, that begins to show corresponding large random fluctuations. This is not at all what the customary cause–effect model would predict.

Two major points are illustrated here. One is that more than one input quantity can be defined in a given experimental situation. The other is that the regularities we commonly term *behavior* are more likely in a natural environment to be associated with inputs than with outputs. Outputs reflect disturbances as well as the actions required to produce a given input pattern, and the component of output reflecting nothing more than disturbances may be by far the larger component. This fact may suggest why behavioral science so often has to rely on statistical methods to deal with its subject matter.

Experiment 4: The Behavioral Illusion

The conditions of Experiment 1 are now restored, and the computer is programmed to insert a nonlinear function between actual handle position and the effect of the handle on cursor position. This nonlinear function is the g function previously defined. Its form here is

$$g(x) = Ax + Bx^3.$$

The polynomial V is thus $A + Bx^2$. A and B are chosen so that the minimum value of V, at the center of the screen, is one third of the maximum value at the boundaries.

If we call q_i^* zero, whatever its magnitude, and refer measures of q_i to that zero point, we can interpret Equation 7a to predict

$$q_o = g^{-1}[-h(q_d)].$$

Instead of computing the unwieldly inverse, we can simply plot q_o against q_d, for it is predicted that

$$Aq_o + Bq_o^3 = -q_d, \text{ where } q_i^* = 0.$$

A typical result for any practiced subject is drawn in Figure 6. The RMS error between q_i and q_i^* remains about 2% of full scale. Most subjects notice nothing different about this rerun of Experiment 1. They are not paying attention to their outputs, except when actions become extreme because of a peak in the disturbance.

A more extreme version of the experiment involves choosing A and B to give the cubic form a reversal of slope near the center of the screen (see Figure 7). Most subjects do notice something different now: A few have complained that the handle is broken or that the computer is malfunctioning, although

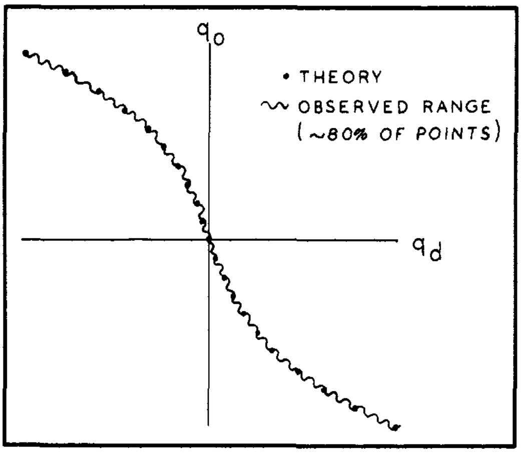

Figure 6. Experiment 4 results drawn from the cathode-ray tube display of the data, with a mildly nonlinear feedback connection. (Handle position is related to disturbance magnitude according to the inverse of the feedback connection. Dots represent the calculated inverse. Wavy lines show the approximate range of 300 data points for the practiced subject. The output quantity is represented by q_o. The disturbing quantity is represented by q_d.)

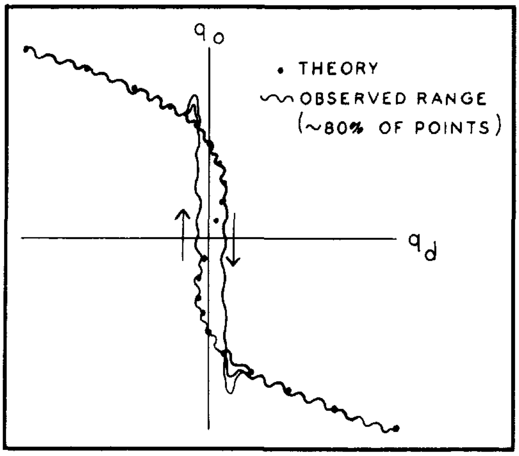

Figure 7. Experiment 4 results drawn from the cathode-ray tube display of the data, with an extremely nonlinear feedback connection (two-valued near center). (Subject's behavior [wavy lines] follows theoretical inverse, except near the center, where the region of positive feedback is skipped over. The output quantity is represented by q_o. The disturbing quantity is represented by q_d.)

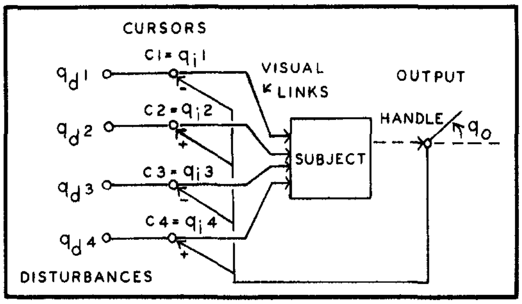

Figure 8. Analytical model for Experiment 5. (The subject sees four independently disturbed cursors [C1 through C4] on the cathode-ray tube. The handle affects all four cursors by an equal amount but in opposite directions for odd and even cursors. The subject can use the handle to control any one of [at least] 16 different aspects of the display.)

when they stop complaining they perform just as well as anyone else.

The reversal of slope converts the nominally Type N relationship to Type P near the center of the screen. Subjects simply skip across the Type P region as quickly as they can to the next stable point, where the feedback is once again negative. Over the rest of the range, the behavior is precisely what is predicted from the inverse of the g function.

A computer simulation using the successive-state method and a value of K chosen for stability behaves in just the same way, whether the behaving system is assumed linear or nonlinear. In fact, a three-level model I tried produced results indistinguishable from those for a real subject except for the very first move. The model had about 2% random noise in it.

The point of both versions of Experiment 4 is to show that the apparent form of the "behavioral law" connecting the distal disturbance to the behavior is determined strictly and quantitatively by the inverse of the feedback function and is, therefore, a property of the environment and not of the subject.

When these nonlinear feedback functions are used in Experiment 3, the subject still succeeds, although not as well, at maintaining a regular input pattern. A bystander entering at that point would have difficulty believing that the motions of the control handle had anything to do with the patterns on the screen. Yet the N-system equations sort out all effects neatly and quantitatively, with little random variation left over. It is all a matter of wearing the right pair of glasses.

Experiment 5: Multiple Choice

Now the display shows four side-by-side cursors instead of one, each moving up and down in its own band under the influence of its own independent random disturbance. The handle position contributes equally to the positions of all four cursors but affects Cursors 1 and 3 (C1 and C3) in the opposite direction to the effects on C2 and C4 (see Figure 8).

The subject is asked to pick any one cursor and hold it as steady as possible somewhere within its range of up–down travel. The subject does so, with results indistinguishable from those of Experiment 2. One of the four cursors remains at the position q_i^* determined with all disturbances set to zero, while the other three cursors wander unsystematically up and down.

All cursors are input quantities; all are imaged on the subject's retinas. Only one, however, is a controlled input quantity. We can now distinguish controlled from uncontrolled input quantities and illustrate the *test for the controlled quantity,* which is a tool for investigating N systems of all kinds.

There are many possible variations of the test. One that works well for these experiments involves treating both handle movements and disturbances as random variables and comparing the expected variance, V_{exp}, of each controlled quantity with the observed variance, V_{obs}. Of course these variances must be calculated taking into account the hypothesized nature of the input quantity to be tested. The expected variance is computed by adding in quadrature the contributions from observed handle position and observed disturbances, appropriately computed on the basis of analyzing the physical situation. Then, a stability factor S is calculated:

$$S = 1 - (V_{exp}/V_{obs})^{\frac{1}{2}}.$$

If $S = 0$, the input quantity is not controlled. If S is positive, behavior destabilizes the input quantity, and positive feedback exists. If S is negative, behavior stabilizes the input quantity, and negative feedback exists. For S several standard deviations more negative than -1, the behaving system can be called an ideal control system. For experiments like the first three, S is typically -4 to -9 for the controlled cursor, implying that the chances against an N system existing range from one in thousands to one in billions. For uncontrolled cursors, S ranges from $+1$ to -1 on short runs and comes close to 0 on long (10-minute) runs.

This statistical version of the test should be useful in cases where behavior takes place in a natural environment, where there are many possible effects of behavior, many sources of disturbance, and many potentially controlled quantities affected both by behavior and by disturbances. Once a controlled quantity has been found by this statistical approach, use can be made of the more quantitative methods of analysis previously discussed.

Any version of the test for the controlled quantity must be followed by verifying that an apparent controlled quantity must be sensed by the behaving system in order to be controlled. In the present experiments, covering up the appropriate cursor with a cardboard strip should, and does, cause the controlled quantity to become an uncontrolled one. Covering any or all of the other cursors has no effect at all.

Experiment 6: More-Abstract Controlled Quantities

Under the same conditions as Experiment 5, the subject is asked to hold constant some other aspect of the display (not specified by the experimenter) rather than the position of one of the cursors. Most subjects are initially baffled by this request, some permanently until given broad hints. Eventually, most see the possibilities of the fact that the handle affects odd and even cursors oppositely. One aspect is the difference in position between an odd and an even cursor. A subject can easily keep, say, C1 and C4 level with each other or C1 a fixed distance above or below C4. Both cursors wander up and down but always together. With suitable definitions, a controlled quantity can be found that unequivocally passes the test for the controlled quantity (four possibilities of this type exist).

Another type of controlled quantity is the configuration with three cursors lying along a straight line. Four possible controlled quantities of this type exist. Still another involves creating a fixed angle with one cursor centered at the vertex and the other two lying in the sides of the angle. All these are relatively easy to control once the subject has realized that they can be seen in the display. Only 1 of these 16 possible static controlled quantities can be controlled at a time because the control handle has only one degree of freedom.

What determines which controlled quantity will be controlled? The apparatus obviously does not, for it determines only the possibilities; not the behavior either—the output, with its single degree of freedom, affects all possible controlled quantities all of the time. The behaving system itself must be the determining factor. What the person attends to becomes the controlled aspect of the display. The person also determines the particular state of the selected aspect that is to serve as q_i^*. My efforts to make models of human organization have been aimed at explaining this type of phenomenon. It has been difficult at times to explain why such models are required when the listener is unaware that such phenomena exist.

In all these experiments, a typical correlation coefficient relating handle position to a noncontrolled quantity or its associated disturbance is in the range from 0 to .8. Statistics are poor in these short runs, but some correlations do occur even in long runs. The handle and the disturbances do affect the various cursors; correlations are to be expected there.

The correlation between a controlled quantity and either its associated disturbance or the handle position is normally lower than .1; a well-practiced subject will frequently produce a correlation of zero to two significant figures. At the same time, the correlation between magnitude of disturbance and handle position is normally higher than .99 (I can often reach .998 in the simpler experiments). To appreciate the meaning of these figures, one has to remember that the subject cannot sense any of the disturbances except through their effects on the input quantities, the cursor positions.

If the controlled input quantity shows a correlation of essentially zero with the behavior, any standard experimental design would reject it as contributing nothing to the variance of behavior. But the disturbance that contributes essentially 100% of the variance of the behavior can act on the organism only via the variable that shows no significant correlation with behavior. Not only the old cause–effect model breaks down when one is dealing with an N system, the very basis of experimental psychology breaks down also.

Summary and Conclusions

I have examined in this article four mistakes that threw cybernetics off the track as far as psychology is concerned: (a) thinking of control theory as a machine analogy, (b) focusing on objective consequences of behavior of no importance to the behaving system itself, (c) misidentifying reference signals as sensory inputs, and (d) overlooking purposive properties of human behavior in man–machine experiments. Considering behavior, without going through any technological analogy, I have developed two mathematical tools for analyzing and classifying behaving organisms. The classical cause–effect model is included as a special case. Finally, I have introduced six experiments that illustrate classes of phenomena peculiar to control behavior and that cannot be explained under any paradigm but the control system model. (The last statement can be taken as a friendly challenge.)

I believe that the concepts and methods explored here are the basis for a scientific revolution in psychology and biology, the revolution promised by cybernetics 30 years ago but delayed by difficulties in breaking free of older points of view. Kuhn (1970) uses the term *paradigm* in the sense I mean when I say that control theory is a new paradigm for understanding life processes—not only individual behavior but the behavior of biochemical and social systems. Chapter X in Kuhn's book discusses "Revolutions as Changes in World View." The experiments we have seen here, while not of great importance in themselves, represent my attempt to show how control theory allows us to see the same facts of behavior that have always been seen but through new eyes, new organizing principles, and new views of the world of behavior.

The natural tendency of any human being is to deal with the unfamiliar by first trying to see it as the nearest familiar thing. That is what happened to the basic concepts of cybernetics. It will happen even more pronouncedly in response to the ideas we have looked at here. The difficulties faced by a new paradigm, as Kuhn explained so clearly, result not from battles over how to explain particular conceptual puzzles, but from bypassing altogether old puzzles that some people insist for a long time still need solving. There are still many fruitful areas of research and many unsolved problems concerning the properties of phlogiston. Modern observational and data-processing techniques in astronomy could lead to great (but unwanted) improvements in the predictive accuracy of the epicycle model of planetary motions (I knew a graduate student in astronomy who showed how well epicycles could work with the aid of a large computer).

Control theory bypasses the entire set of empirical problems in psychology concerning how people tend to behave under various external circumstances. One kind of behavior can appear under many different circumstances; instead of comparing all the various kinds of causes with each other while looking for objective similarities to explain the common effects, we are led by control theory to look for the *inputs* that are disturbed not only by the discovered causes but by all possible causes. For a thousand unconnected empirical generalizations based on superficial similarities among stimuli, I here substitute one general underlying principle: *control of input.*

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