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Human Factors in Decision and Control: Nonstandard Modeling and Information Processing

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ABSTRACT

The study of human factors is increasingly important in information science and technology for studying the foundations of man-machine systems and also for medical research and applications. The time is not yet ripe to form a complete foundation of human factors concerning human information processing, particularly the infrastructure and mechanism of brainware, but it is time to provide some—though by no means all—foundations of human factors science as explicit and well established as those for the internal dynamics of humans, and to make suggestions for human-computer interaction in decision-making analysis. In this paper the study of human factors and related topics in information science and technology is advanced through the construction of an advanced control system, namely, the triple {man, machine, environment}, and the establishment of the formalism of this complex system by using the fuzzy set theories, such as general theories of fuzzy topology, sequences of fuzzy sets, fuzzy-continuous functions, compact fuzzy spaces, lattice of continuities of fuzzy topological space, and not least, fuzzy filters. Human-factors modeling can be based on oriental medical theories, namely, the five-elements theory and the Yin-Yang theory; fuzzy set and system theories have been applied to create the analytical expression for the model. Two examples are furnished as possible applications of these ideas: a model for estimation of the human state, and one for the man-computer interaction in decision-making analysis.

1. INTRODUCTION

Recently, many technological and health-care systems have become highly automated [13, 15, 18, 21, 25, 30, 31, 38–41, 43–45, 51, 53, 54], so that human and technical systems form a unified functional unit (Figure 1). In this situation human skill and computer calculations provided by technology supplement each other. The quality of information processed by such systems depends on the capability of the computer and on the ability of the human to process the information. Therefore, both factors should be considered in systems interaction. So far, the computer-using side has been developed in many investigations

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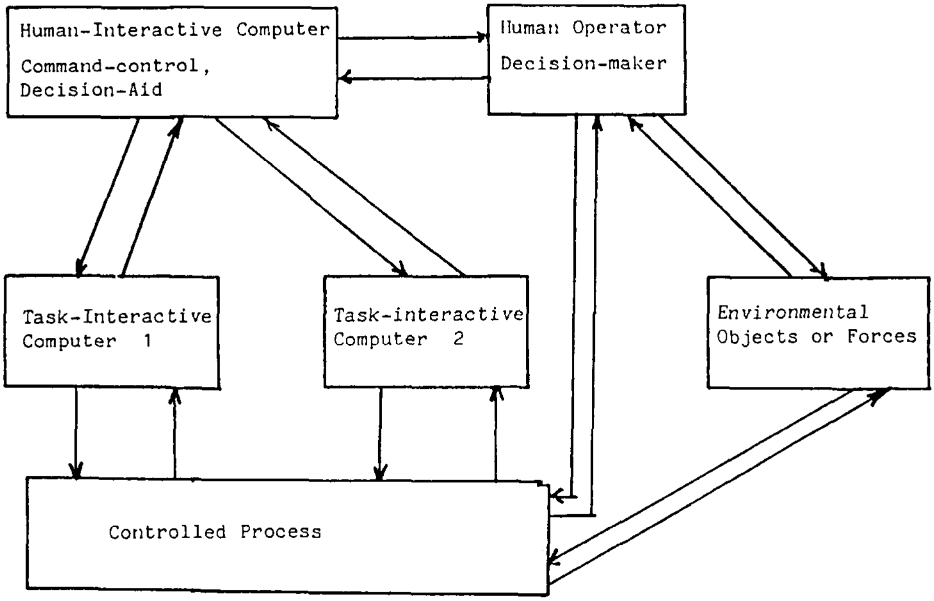


Fig. 1. Schematic representation of a man-machine system.

[7, 14, 38, 40], while the human-operator side has yet to receive attention [28, 30]. In this study we strive to deal with some problems of the human operator.

At the beginning of his book *Cybernetics*, Norbert Wiener defined cybernetics as "control and communication in the animal and in the machine" [50]. I believe that one can safely say that for the problem of information and control in machines there exist successful methods which have been investigated since the fifties [1–3, 6, 11–14, 26, 31, 33, 38, 42, 46], but for the question of information and control in animals (humans) the investigation is just beginning [4, 5, 10, 17, 19, 22–26, 28, 34, 35, 39, 41, 45].

For the information and control problem in machines there is a long tradition within systems analysis for computer calculations, with development and design based upon different mathematical optimal-control models, which are successfully applied to many technical and nontechnical systems. Some of these applications include spaceship control, nuclear-reactor control, chemical production control, modeling and control of agricultural production, modeling and control of endocrine-metabolic systems, etc. In this paper we will not deal with those problems. The reader should refer to [1–3, 11, 12, 14, 15, 26, 31, 36, 38, 42, 46, 51] for a detailed discussion of these questions.

The main purpose of this work is to elaborate a fundamental method for investigation of human issues in man-computer interaction decision-making analysis—specifically, the problem of the reliability and satisfaction of system functions. Highly automated production gives high productivity and quality of products, but requires not only high investment but also a high quality of man-machine control, especially for the human operator. An accident by an operator using a classical machine may result in a localized and small loss, but an accident caused by a human operator in a computer-aided flexible manufacturing system may destroy the whole system and more.

To increase the quality of such systems, humans need support to maintain satisfactory working conditions and means for coping with all possible unforeseen states of affairs or poorly designed control programs. The high risk of accidents in large and complex centralized-care management has increased concerns about the ability to predict human performance during complex rare events and under stressful and unpleasant working conditions. However, it is necessary to systematically consider human performance as a whole, from the observed information on genetic problems, biochemical response, physiological state, and psychological state. The formulations should include a large number of work situations from routine daily activity to stressful encounters with potentially dangerous consequences. Therefore this work strives to formulate the relationship between human dynamics (including biochemical response and physiological state) and human ergonomics (including psychological state and human problem solving).

Also, if an engineer develops and designs a system off line with a video display terminal and he runs into a problem, he can stand up and leave the work if he has to. But what do you do if the problem arises for a machine operator in a spaceship, in deep-sea exploration, or in a nuclear power reactor?

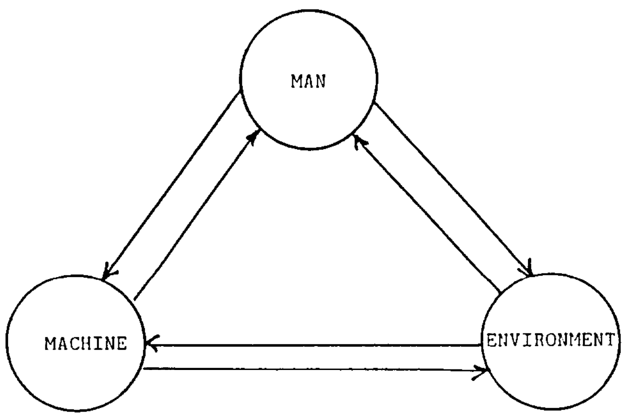


Fig. 2. Representation of relation between man, machine, and environment.

How can we help such an operator? This can be achieved by modernizing communication techniques, or by improving the physiological/biochemical status, or by increasing knowledge through learning and training methods, or by constructing a man-computer system which is comfortable for the user to operate. With all these questions we are concerned with the problem of the human operator and related topics in man-machine systems under the influence of their environment (Figure 2). Some important variables of such relations may be given as follows:

Human to environment:

Friendly construction of environment.
Industrial waste etc.

Environment to human:

Air (O_2, temperature, humidity).
Water (O_2, clean).

Human to machine:

Adequate knowledge for work.
Work experience.

Machine to human:

Complexity.
Control language (e.g., English in countries where people don't speak English).
Technical equipment for information reception and use.

Environment to machine:

Tropical conditions.
Space, deep sea, etc.

Machine to environment:

CO_2.
Noise.

In this study we cannot discuss all these questions of the triple system man, machine, environment, so we will deal with some problems of man-machine systems with regard to environmental conditions.

In general there are two main problems to be considered in studying human aspects of control systems: first, the technical tools for measuring received information, and second, the basic methods for simulation and training.

For technical tools one can use the well-known measuring methods based on biopotentials, such as the electroencephalogram (EEG), electrocardiogram (ECG), electroneurogram (ENG), electromyogram (EMG), and electroretinogram (ERG) [25, 26, 47, 48]. In addition, some new methods and medicines for the study of human aspects are currently being researched, developed, and tested. These are, for example, measuring methods based upon temperature/ bioelectric phenomena at acupuncture points (EAG for short) [5, 22–24, 55], and methods for measuring the physical field of biological objects [4, 10, 34].

Obviously, most biosignals are small, and it is very difficult to carry out exact measurements. If we combine medical instruments with microcomputers, then signal filtering and self-calibration for measurement systems, and automatic processing of human biodata, can be flexibly realized and easily improved by implementation of software systems. However, these software systems must be suitable for computer utilization. These are the more difficult and fundamentally interesting problems in the human aspect and related man-machine systems. For example, a key question is how to formulate the transformation from measured biosignals into informative messages about human cognitive ability and skilled decisionmaking.

In this work we propose to discuss the application of fuzzy set and possibility theory to information modeling of the abovementioned human issues, which will be presented in Section 3. For the foundations of this study some main topics of fuzzy set theory will be given in Section 2. Two typical applications, namely, an estimation model for the human state and human decision-making analysis in man-computer interaction control, will be discussed in Section 4.

2. FOUNDATIONS OF FUZZINESS

The application of fuzzy-set and possibility theory as a foundation for the study of decisionmaking analysis in man-computer systems makes it possible to consider issues which cannot be dealt with effectively and/or correctly by conventional techniques. This is especially true when dealing with human decisionmaking analysis [1, 15, 16, 18, 20, 21, 28, 30, 31, 40, 41, 54]. From the various questions to be dealt with in the modeling and control of such systems, the quantified statement of fuzzy probability measure and the calculation operant for information estimation and decisionmaking analysis are very important. The present section proposes a systematic representation of these problems and strives to build a unified framework for investigation.

Therefore, in this section essential results of the fuzzy-set and possibility theory of man-computer systems will be pulled together from many publications [2, 6, 8, 9, 13–15, 23, 29, 33, 52–54]. They are necessary for understanding the remaining sections of this paper.

2.1. FUZZY TOPOLOGICAL SPACE

Let $X = \{x\}$ be a space of points. Informally, we define a fuzzy set A in X as a subspace with fuzzy boundaries characterized by a membership function that associates with each x its grade of membership $\mu_A(X)$ in A. Assume that $\mu_A(x)$ is a function of x from A to the unit interval [0, 1], as in the research of Zadeh [52].

Before we start to deal with topological properties of fuzzy sets, let us concern ourselves with some essential calculations for membership functions $\mu_A(x)$ as follows: If A, B are fuzzy sets, then

$$A = B \quad \text{if and only if} \quad \mu_A(x) = \mu_B(x), \tag{2.1}$$

$$A \subseteq B \quad \text{if and only if} \quad \mu_A(x) \leqslant \mu_B(x), \quad \forall x \in X. \tag{2.2}$$

In the case $\mu_A(x) < \mu_B(x)$ (i.e., the inequality is strict), we have the strict inclusion $A \subset B$, and

$$\mu_{A \wedge B}(x) = \min(\mu_A(x), \mu_B(x)), \tag{2.3}$$

$$\mu_{A \vee E}(x) = \max(\mu_A(x), \mu_B(x)), \tag{2.4}$$

$$\mu_A(x) = \mu_A(x) - \mu_B(x) \qquad \text{when} \quad \mu_A(x) \geqslant \mu_B(x). \tag{2.5}$$

The scalar cardinal of fuzzy set A can be defined by

$$|A| = \sum_{x \in X} \mu_A(x), \tag{2.6}$$

or, if there is no confusion, $|A|$ can be called A. Therefore we obtain

$$|\tilde{A}| = X - A, \tag{2.7}$$

$$A \wedge B + A \vee B = A + B. \tag{2.8}$$

The main operators are the infimum defined by

$$\mu(x)_i = \inf \mu(x, y) \qquad \text{for all} \quad x \in X, \quad y \in Y, \tag{2.9}$$

the supremum defined by

$$\mu(x)_s = \sup \mu(x, y) \qquad \text{for all} \quad x \in X, \quad y \in Y, \tag{2.10}$$

the algebraic product defined by

$$AB \quad \leftrightarrow \quad \mu_{AB}(x) = \mu_A(x)\mu_B(x), \tag{2.11}$$

and the algebraic sum defined by

$$A +\circ B \quad \leftrightarrow \quad \mu_A(x) + \mu_B(x) - \mu_A(x)\mu_B(x). \tag{2.12}$$

The main properties are the reflexivity

$$\mu(x,x) = 1 \qquad \text{for all} \quad x \in X, \tag{2.13}$$

the symmetry

$$\mu(x,y) = \mu(y,x) \qquad \text{for all} \quad x, y \in X, \tag{2.14}$$

and the transitivity

$$\mu(x,z) \geqslant \sup\min\{\mu(x,y), \mu(y,z)\} \qquad \text{for all} \quad x, y, z \in X. \tag{2.15}$$

The numerical calculation may be realized by fuzzy variables for all $a, b \in [0,1]$. Then

$$a \vee b + a \wedge b = a + b, \tag{2.16}$$

$$a \vee b = \max(a,b), \tag{2.17}$$

$$a \wedge b = \min(a,b), \tag{2.18}$$

$$a \vee b = a + b - ab, \tag{2.19}$$

$$a \wedge b = ab, \tag{2.20}$$

$$0 \wedge 0 = 0, \tag{2.21}$$

$$a \wedge 1 = 1 \wedge a = a, \tag{2.22}$$

$$\text{if} \quad a \leqslant c,\ b \leqslant d, \quad \text{then} \quad a \wedge b \leqslant c \wedge d, \tag{2.23}$$

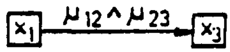
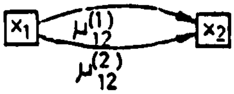
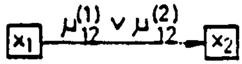
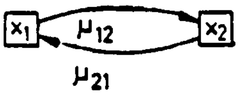
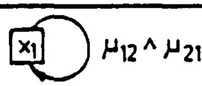
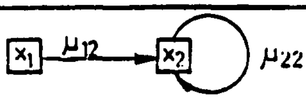
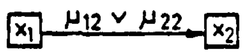
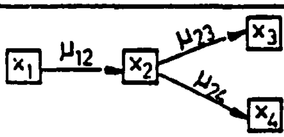
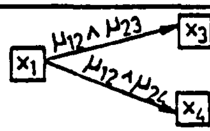
$$a \wedge b = b \wedge a, \tag{2.24}$$

$$a \wedge (b \wedge c) = (a \wedge b) \wedge c. \tag{2.25}$$

Furthermore, some basic calculations from [23], which are constitutive calculations for experimental measurement of human states, are introduced in Table 1.

Now we will discuss the topological properties of fuzzy set theory.

TABLE 1

1	 $x_2 = \mu_{12} \wedge x_1$ $x_3 = \mu_{23} \wedge x_2$	 $x_3 = (\mu_{12} \wedge \mu_{23}) \wedge x_1$
2	 $x_2 = (\mu_{12}^{(1)} \wedge x_1) \vee (\mu_{12}^{(2)} \wedge x_1)$	 $x_2 = (\mu_{12}^{(1)} \vee \mu_{12}^{(2)}) \wedge x_1$
3	 $x_2 = \mu_{12} \wedge x_1$ $x_1 = \mu_{21} \wedge x_2$	 $x_1 = (\mu_{12} \wedge \mu_{21}) \wedge x_1$
4	 $x_2 = (\mu_{12} \wedge x_1) \vee (\mu_{22} \wedge x_2)$	 $x_2 = (\mu_{12} \vee \mu_{22}) \wedge x_1$
	 $x_2 = \mu_{12} \wedge x_1$ $x_3 = \mu_{23} \wedge x_2$ $x_4 = \mu_{24} \wedge x_2$	 $x_3 = (\mu_{12} \wedge \mu_{23}) \wedge x_1$ $x_4 = (\mu_{12} \wedge \mu_{24}) \wedge x_1$

DEFINITION 1. A fuzzy topology is a family F of fuzzy sets in X which fulfills the conditions

$$\varnothing, X \in F, \tag{2.26}$$

$$\text{if} \quad \text{fuzzy sets } A, B \in F, \quad \text{then} \quad A \cap B \in F, \tag{2.27}$$

$$\text{if} \quad A_i \in F \quad \text{for each } i \in N, \quad \text{then} \quad \bigcup_N A_i \in F, \tag{2.28}$$

where $\varnothing$ denotes an empty fuzzy set with $\mu_0(x) = 0$ for all x in X, and for X we have $\mu_X(x) = 1$. The pair (X, F) is called a fuzzy topological space. A member of F is called an F-open fuzzy set. A fuzzy set is F-closed if and only if its complement is F-open. In addition, a fuzzy topology G is said to be coarser then a fuzzy topology F if and only if $G \subset F$.

DEFINITION 2. A fuzzy set G in a fuzzy topological space (X, F) is a neighborhood of a fuzzy set A if and only if there exists an open fuzzy set O such that $A \subset O \subset X$.

THEOREM 1. *A fuzzy set A is open if and only if for each fuzzy set B contained in A, A is a neighborhood of B.*

THEOREM 2. *If G is the neighborhood system of a fuzzy set, then finite intersections of members of G belong to G, and each fuzzy set which contains a member of G belongs to G.*

DEFINITION 3. Let A and B be fuzzy sets in a fuzzy topological space (X, F), and let $B \subset A$. Then B is called an interior fuzzy set of A if and only if A is a neighborhood of B. The union of all interior fuzzy sets of A is called the interior of A and is denoted by A°.

THEOREM 3. *Let A be a fuzzy set in a fuzzy topological space (X, F). Then A° is open and is the largest open fuzzy set contained in A. The fuzzy set A is open if and only if $A = A^\circ$.*

2.2. SEQUENCES OF FUZZY SETS

DEFINITION 4. A sequence of fuzzy sets, say $\{A_n,\ n = 1, 2, \ldots, N\}$, is eventually contained in a fuzzy set A if and only if there is an integer m such that if $n \geqslant m$ then $A_n \subset A$. The sequence is frequently contained in A if and only if for each integer m there is an integer n such that $n \geqslant m$ and $A_n \subset A$. If the sequence is in a fuzzy topological space (X, F), then we say that the sequence converges to a fuzzy set A if and only if it is eventually contained in each neighborhood of A.

DEFINITION 5. Let N be a map from the set of nonnegative integers to the set of nonnegative integers. Then the sequence $\{B_i,\ i=1,\dots,N\}$ is a subsequence of the sequence $\{A_n,\ n=1,\dots,N\}$ if and only if there is a map N such that $B_i = A_{N(i)}$ and for each integer m there is an integer n such that $N(i) \geqslant m$ whenever $i \geqslant n$.

DEFINITION 6. A fuzzy set A in a fuzzy topological space (X, F) is a cluster fuzzy set of a sequence of fuzzy sets if and only if the sequence is frequently contained in every neighborhood of A.

THEOREM 4. *If the neighborhood system of each fuzzy set in a fuzzy topological space (X, F) is countable, then:*

(a) *A fuzzy set A is open if and only if each sequence of fuzzy sets $\{A_n, n=1,\dots,N\}$ which converges to a fuzzy set B contained in A is eventually contained in A.*

(b) *If A is a cluster fuzzy set of a sequence $\{A_n,\ n=1,\dots,N\}$ of fuzzy sets, then there is a subsequence of the sequence converging to A.*

2.3. *FUZZY-CONTINUOUS FUNCTIONS*

In this section, the continuity of a fuzzy function will be generally characterized.

DEFINITION 7. Let f be a function from X to Y. Let B be a fuzzy set in Y with membership function $\mu_B(y)$. Then the inverse of B, written as $f^{-1}(B)$, is a fuzzy set in X whose membership function is defined by

$$\mu_{f^{-1}[B]}(x) = \mu_B(f(x)) \qquad \text{for all } x \text{ in } X. \tag{2.29}$$

Furthermore, let A be a fuzzy set in X with membership function $\mu_A(x)$. The image of A in Y is a fuzzy set B whose membership function is given by

$$\mu_B(y) = \begin{cases} \sup_{x \in f^{-1}(y)} \mu_A(x) & \text{if } f^{-1}(y) \text{ is not empty,} \\ 0 & \text{otherwise} \end{cases} \tag{2.30}$$

for all y in Y, where $f^{-1}(y) = \{x \mid f(x) = y\}$.

THEOREM 5. *Let f be a function from X to Y. Then*

$$f^{-1}[B'] = \{f^{-1}[B]\}' \qquad \textit{for any fuzzy set } A \textit{ in } X; \tag{2.31}$$

$$f[A'] \subset \{f[A]\}' \qquad \textit{for any fuzzy set } A \textit{ in } X; \tag{2.32}$$

$$\textit{if} \quad B_1 \subset B_2 \quad \textit{then} \quad f^{-1}[B] \subset f^{-1}[B], \tag{2.33}$$

where B_1, B_2 *are fuzzy sets in* Y;

$$\text{if} \quad A_1 \subset A_2 \quad \text{then} \quad f[A]_1 \subset f[A]_2, \tag{2.34}$$

where A_1 *and* A_2 *are fuzzy sets in* X;

$$B \supseteq f\{f^{-1}[B]\} \qquad \text{for any fuzzy set } B \text{ in } Y; \tag{2.35}$$

$$A \subset f\{f^{-1}[A]\} \qquad \text{for any fuzzy set } A \text{ in } X. \tag{2.36}$$

Let f *be a function from* X *to* Y *and* g *be a function from* Y *to* Z. *Then* $(g \circ f)^{-1}[C] = f^{-1}\{g^{-1}[C]\}$ *for any fuzzy set* C *in* Z, *where* $g \circ f$ *is the composition of* g *and* f.

Therefore, we can now define fuzzy continuity as follows:

DEFINITION 8. A function f from a fuzzy topological space (X, F) to a fuzzy topological space (Y, G) is fuzzy-continuous if and only if the inverse of each G-open fuzzy set is F-open.

Hence, if f is a fuzzy-continuous function from X to Y, and g is a fuzzy-continuous function from Y to Z, then the composition $g \circ f$ is a fuzzy-continuous function from X to Z. Obviously, we have

$$(g \circ f)^{-1}[C] = f^{-1}\{g^{-1}[C]\} \qquad \text{for each fuzzy set } C \text{ in } Z. \tag{2.37}$$

2.4. *COMPACT FUZZY SPACES*

The discussion of compactness of a fuzzy topological space starts with the following definitions.

DEFINITION 9. A family $\mathscr{G}A$ of fuzzy sets is a cover of a fuzzy set B if and only if $B \subset \bigcup\{A \mid A \in \mathscr{G}A\}$. It is an open cover if and only if each member of $\mathscr{G}A$ is an open fuzzy set. A subcover of $\mathscr{G}A$ is a subfamily of $\mathscr{G}A$ which is also a cover.

DEFINITION 10. A fuzzy topological space (X, F) is compact if and only if each open cover has a finite subcover.

DEFINITION 11. A family $\mathscr{G}A$ of fuzzy sets has the finite-intersection property if and only if the intersection of the members of each finite subfamily of $\mathscr{G}A$ is nonempty.

The compactness of a fuzzy topological space is then characterized in following theorem.

THEOREM 6. *A fuzzy topological space is compact if and only if each family of closed fuzzy sets which has the finite-intersection property has a nonempty intersection.*

THEOREM 7. *Let f be a fuzzy-continuous function carrying the compact fuzzy topological space X onto the fuzzy topological space Y. Then Y is compact.*

2.5. LATTICE OF CONTINUITIES OF FUZZY TOPOLOGICAL SPACE

Let X be a set, and let A be a fuzzy set on X. We now define several sets related to the construction of a lattice as follows: the characteristic set of A defined by

$$C(A) = \{x | \mu_A(x) \geqslant 0 \text{ for all } x \in X\}, \tag{2.38}$$

the zero set of A defined by

$$Z(A) = \{x | \mu_A(x) = 0 \text{ for all } x \in X\}, \tag{2.39}$$

and the unit set of A defined by

$$U(A) = \{x | \mu_A(x) = 1 \text{ for all } x \in X\}. \tag{2.40}$$

DEFINITION 12. A fuzzy lattice is a nonempty fuzzy set with a reflexive partial ordering $\geqslant$ such that for every pair x, y of members of X, there is a smallest element $\max(\mu(x), \mu(y))$ which is greater than each of $\mu(x)$ or $\mu(y)$ and a largest element $\min(\mu(x), \mu(y))$ which is smaller than each.

DEFINITION 13. A lattice is distributive if and only if

$$\mu(x) \wedge [\mu(y) \vee \mu(z)] = [\mu(x) \wedge \mu(y)] \vee [\mu(x) \wedge \mu(z)], \tag{2.41}$$

$$\mu(x) \vee [\mu(y) \wedge \mu(z)] = [\mu(x) \vee \mu(y)] \wedge \mu(z) \tag{2.42}$$

for all x, y, z in X.

DEFINITION 14. A fuzzy set A of set X is an ideal if and only if whenever $\mu(y) \geqslant \mu(x)$ and $y \in A$, then $x \in A$, and if y and z belong to A, so does

$$\arg\max(\mu(y), \mu(z)) \in A. \tag{2.43}$$

If $x, y, z \in A$, then whenever $\mu(x) \geqslant \mu(y)$,

$$\arg\min(\mu(y), \mu(z)) \in A. \tag{2.44}$$

It should be noticed that the above definitions on a lattice of continuities of fuzzy topological space are very useful for fuzzy pattern recognition.

2.6. *FUZZY FILTER*

A fuzzy filter F in set X is a family of nonempty fuzzy sets of X such that

$$\text{if} \quad A, B \in X, \quad A \in F, \text{ and } A \leqslant B, \quad \text{then} \quad B \in F, \tag{2.45}$$

and the intersection of two members of F always belongs to F, that is, if $A \in F$ and $B \in F$, then $A \wedge B \in F$.

A filter basis β is a family of fuzzy sets satisfying the condition that for every $A \in \beta$ there is $C \in \beta$ such that $A \wedge B \geqslant C$. If F_1 and F_2 are two fuzzy filters, we say that F_1 redefines F_2 if $F_1 \supset F_2$. If F_1 is generated by the filter basis β_1 and F_2 by β_2, the condition $F_1 \supset F_2$ is trivially equivalent to the assertion that for every $B_2 \in \beta_2$, one can find $B_1 \in \beta_1$ such that $B_1 \leqslant B_2$. A filter F is called an ultrafilter if it is not redefined by any filter but itself.

We will now discuss some properties of the convergence of fuzzy filters. A fuzzy filter F converges to a point x in a fuzzy topological space X if and only if each neighborhood of x is a member of F. A fuzzy set V is open if and only if V belongs to every filter which converges to a point of V. A point x is an accumulation point of a fuzzy set A if and only if $A \setminus |x|$ belongs to some filters which converge to x. Let $\mathscr{C}_x$ be the collection of all filters which converge to a point x; then $\bigcap\{F\colon F \in \mathscr{C}_x\}$ is the neighborhood system of x. If F is a fuzzy filter converging to x and G is a fuzzy filter which contains F, then G converges to x. The aim of this brief discussion on fuzzy filters is to develop a foundation for building fuzzy estimation, which helps us to obtain reliable information from fuzzy measurements.

The foregoing consideration is based upon the axioms represented in Equations (2.1) to (2.6) and fundamental calculations given in Equations (2.7) to (2.25). These expressions are to create the confident basis for the considerations in Sections 3 and 4, in which the main attention is addressed to the *power* of the events. Obviously, one can build other axiomatic systems for research, but we stay in this foundation because there are successful results which are based on the axiomatic system shown in Equations (2.1) to (2.6) [13–21, 29, 33, 34].

One can say that the abovementioned results are only necessary, but by no means sufficient, for the study of dynamic systems with respect to their uncertainty. For the sufficiency we will deal with the *entropy* of systems, that means we will be concerned with stability and validity, and chaos and confusion. There are some precedents for an entropy approach to studying dynamical systems, such as the entropy in thermodynamic theory and in Shannon's information theory. For this study we will now introduce two entropy concepts as follows.

Topological Entropy

DEFINITION 15. Let X be a compact topological space. For any open cover $\mathscr{A}$ of X, let $N(\mathscr{A})$ denote the number of sets in a subcover of minimal cardinality. A subcover of a cover is minimal if no other subcover contains fewer members. Since X is compact and $\mathscr{A}$ is an open cover, there always exists a finite subcover. To conform with prior work in ergodic theory we call $H(\mathscr{A}) = \log N(\mathscr{A})$ the entropy of $\mathscr{A}$ [58]. Therefore, we can obtain a general theorem as follows [58].

THEOREM 8. *Entropy is an invariant in the sense that* $H(\nu\mu\nu^{-1}) = H(\mu)$, *where* μ *is a continuous mapping of* X *into itself and* ν *is a homomorphism of* X *onto some* X'.

Evidently, this theorem is general, but it is not so easy to use in a practical calculation, although it seems to provide a theoretically rigorous explanation. We need another concept for calculation. We introduce the definition given by A. D. Luca and S. Termini [59].

Entropy Measure of a Fuzzy Set

DEFINITION 16. Assume that a set fulfills the conditions given in Equations (2.1) to (2.6). In addition assume that for two fuzzy measures μ and ν, the set fulfills the involution law $\neg\neg\mu = \mu$ and the De Morgan laws

$$\neg(\mu \vee \nu) = \mu \wedge \nu \quad \text{and} \quad \neg(\mu \wedge \nu) = \neg\mu \vee \neg\nu.$$

Furthermore, if we denote the class of all fuzzy sets by $\mathscr{L}(X)$, then for each $\mu, \nu \in \mathscr{L}(X)$, the functional $H(\mu)$, called the entropy measure of a fuzzy set, is given by

$$H(\mu) = \sum_{i=1}^{n} \left[-x_i \ln x_i - (1 - x_i)\ln(1 - x_i) \right], \tag{2.46}$$

where x_i is any fuzzy function.

This equation enables the appropriate calculations.

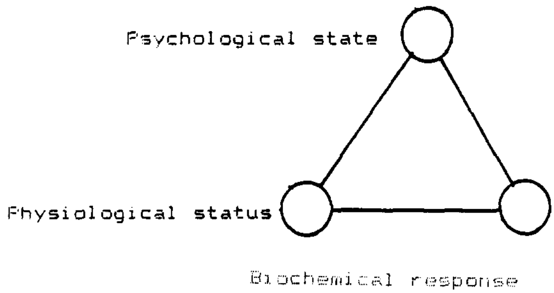


Fig. 3. Representation of the relationship between psychological state, physiological state, and biochemical response of the human dynamics.

3. HUMAN-FACTOR MODELING

In existing man-computer systems, the calculation of human factors is carried out through the use of observation techniques and action control mechanisms [4, 10, 19, 23, 25, 28, 39, 40, 47, 48]. However, it has recently been recognized that these methods have serious shortcomings and, for the most part, are hard to rationalize. What are particularly open to question are first, the universally adopted simulation of the functioning of the three factors: man, machine, environment, (Figure 1 in Section 1); and second, the feedback relation between the psychological state, the physiological state, and the biochemical response of the human operator associated with his current environment, which may be formulated as functions of human beings in control and command systems (Figure 3). One can safely say that study in this field is just beginning [15, 18, 20, 28, 30, 39, 40, 54] and we have a great deal to learn through mathematical modeling, experimentation, and systematic analysis so we can produce reliable human models in control and command systems.

Theoretically, the study of human simulation is based on a four-level construction. In general, such a system may be represented as in Figure 4. First is the genetic level, which explains the process of assembly of a substance. Second is the biochemical level, which explains the synthesis of substances. Third is the physiological level, which reflects the storage and transportation of substances. Fourth is the psychological level, which reflects learning, problem solving, and decision making. Obviously, this is a tremendously difficult research problem. To solve it we must break it down into two main parts. The first one deals with biomedical measurement instruments including computers —in other words, the method for receiving information from human beings. The second is systematic and mathematical models for the formulation of human beings, which means methods to process information. Despite our

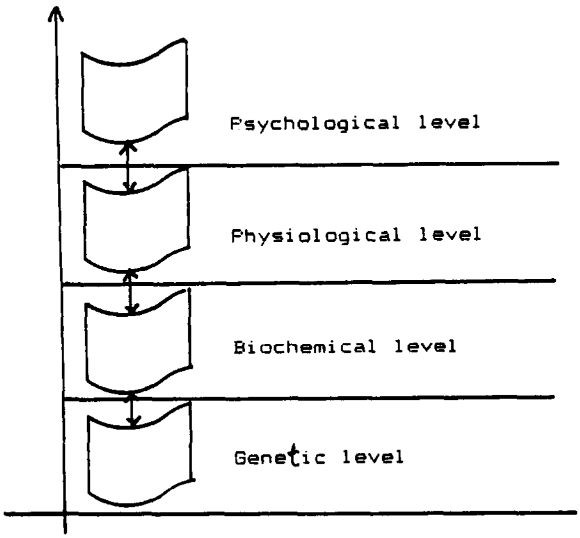


Fig. 4. Axiomatic representation of four human-dynamics levels.

concentration on software problems, a brief discussion of measuring instruments will be furnished for completeness.

3.1. BIOMEDICAL MEASUREMENT INSTRUMENTS

For biomedical and clinical research and for other studies of humans there exist many methods to measure the position of body organs, temperature of the body, blood pressure, color of the skin, etc. Systematic measurements include the electroencephalogram (EEG), electrocardiogram (ECG), electroneurogram (ENG), electromyogram (EMG), and electroretinogram (ERG) [4, 47, 48]. With the recognition of the successful application of acupuncture in medicine, new nonwestern biomedical measurement methods have been developed [5, 22–24, 49, 55]. The general outline of this method, shown in Figure 5, involves mainly transducers, signal-processing devices, and displays to convert information on living systems to a form that a human operator can perceive. Using the definitions of the biomedical measure from Hoang et al. [19, 22, 23] and Webster [47, 48], the physical quantity, property, or condition that the system measures is called the measurand. The accessibility of the measurand is important: it may be internal (blood pressure) or on the body surface (bioelectric potential), or it may emanate from the body (infrared radiation). Most medically important measurands can be grouped into the following categories:

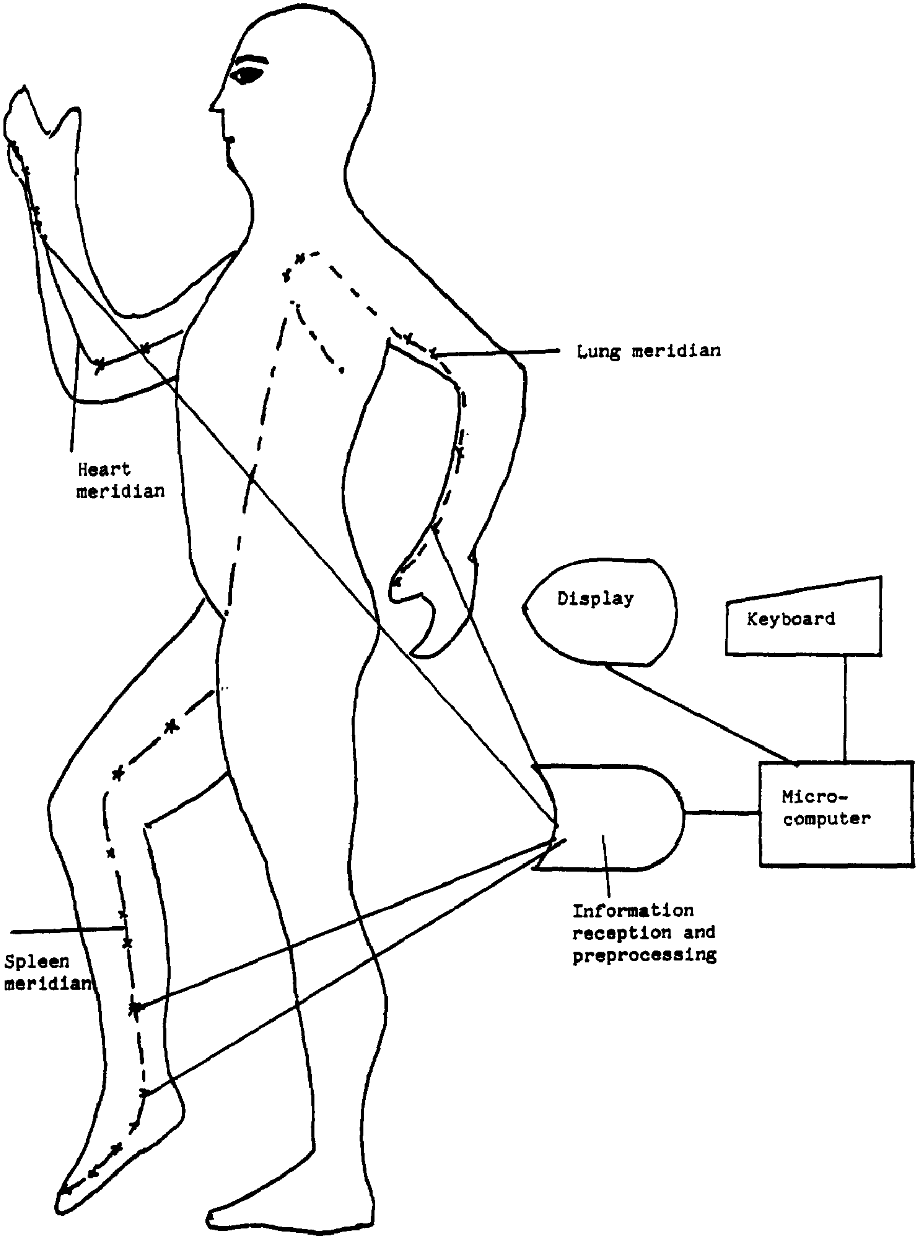


Fig. 5. A scheme for estimation of the relationship of the triple (lung, heart, spleen) by measuring the electropotential at acupuncture points.

potential, impedance, flow, displacement (together with velocity, acceleration, and force), temperature, and chemical concentrations. In the following discussion some applications of these methods will be briefly mentioned, which are easy to carry out with technical equipment and guarantee reliable results.

Temperature Measures

It is well known that the temperature of the human body provides important information about its physiological state with regard to thermal regulation, metabolic processes, and blood circulation. In addition it may furnish direct information about certain diseases, for example, arthritis and other inflammatory diseases. Accurate methods exist for measuring temperature, such as thermocouples, thermistors, and radiation and chemical detectors.

One of the earliest methods was thermoelectric thermometry, in which an electromotive force (emf) exists across a junction of two dissimilar metals. This action results in a voltage which may be represented by

$$E = aT + \tfrac{1}{2}bT^2,$$

where T is in degrees Celsius and $a + bT = dE/dt$ is called the thermoelectric sensitivity. The advantages of thermoelectric thermometers are their fast response (≈ 1 ms), small size (down to 12 μm), ease of fabrication, and long-term stability. They can be inserted into catheters and hypodermic needles.

Radiation thermometry is based upon a relationship between the surface temperature of an object and its radiant energy. With this principle one can measure the temperature of a body without physical contact with it. Using medical thermography the temperature distribution of the skin may be plotted with a sensitivity of a few tenths of a kelvin. Thermography has been used successfully for the early detection of breast cancer, for determining the location and extent of arthritis, and so on. Thus, skin temperatures are observed variables which mirror the state of circulatory and metabolic processes. There is also evidence that the measurement of the temperature at acupuncture points can give important information about a human being's state. Obviously, the main question is how to build a model for the transformation of process variables into observed variables.

Measurement of Blood Pressure

Measured values of an individual's blood pressure provide information about the functional integrity of the cardiovascular system. This is necessary for clinical research and for the study of man-machine systems. One can use both direct and indirect measurement methods.

For direct measurement one can use an extravascular transducer system or an intravascular system. In the extravascular measurement method the vascular pressure is coupled to an external transducer by using a liquid-filled catheter. The advantage of this method is that the measuring equipment has high stability and sensitivity. By using an intravascular transducer the liquid coupling is eliminated, since the transducer is incorporated into the tip of a catheter that is placed in the vascular system.

Indirect measurement of blood pressure provides values of the intraarterial pressure noninvasively. The most frequent technique employed is either palpation or audible detection of the pulse distal to an occlusive cuff.

Since blood-pressure measurements using extravacular transducers or intravascular systems inform one of the functional integrity of the cardiovascular system, it is hoped that these sensors can also be useful in the measure of blood pressure at acupuncture points.

Biopotential Measures

Bioelectric potentials are produced as a result of electrochemical activity of a certain class of cells, known as existable cells, which are components of nervous, muscular, or glandular tissue [25, 26, 47, 48]. The potential of an individual cell is engendered by maintaining a steady electrical potential difference between its internal and external environments, which usually has values in the range -50 to -100 mV. The electric potential in man may be measured by the following methods.

The electroneurogram (ENG) is used for measuring the conduction velocity in a peripheral nerve. One of its useful clinical applications is seeing if the conduction velocity in a regenerating nerve fiber is lowered, which indicates that the nerve is injured.

The electromyogram (EMG) measures muscular movement status. Skeletal muscle is organized functionally as a motor unit. This is the smallest unit which can be activated by a voluntary effort, in which all constituent fibers are activated synchronously. The component muscle fibers of the single motor unit (SMU) constitute a distributed unit bioelectric source located in a volume conductor consisting of all other muscle fibers, both active and inactive. The evoked extracellular field potential from the active fibers of an SMU has a triphastic form of brief duration (3–15 ms) and an amplitude of 20 to 2000 μV depending on the size of the motor unit. The frequency of discharge usually varies from 6 to 30 pulses per second.

The electrocardiogram (ECG) measures the status of the heart. The heart serves as a four-chambered pump for the circulatory system. The main pumping function is supplied by the ventricles, and the atria are merely antechambers to store blood during the time the ventricles are pumping. The coordinated contraction of the atria and ventricles is set up by a specific pattern of electrical activation in the musculature of these structures. Considering the heart as a bioelectric source, the strength of this source may be expected to be directly related to the mass of the active muscle. Therefore, the atria and the free walls and septum of the ventricles can be considered the major contributors to external potential fields from the heart. In electrocardiographic problems, the heart is viewed as an electrical equivalent generator. Therefore, the electrical activity of each region at any instant of time can be thought of as represented by a current dipole and a net dipolar contribution from all active areas determined at the electrical center. The thoracic medium can be considered as the resistive load of this equivalent cardiac generator.

The electroencephalogram (EEG) measures brain activity. The intensities of brain waves on the surface of the brain may be as large as 10 mV, whereas those recorded from the scalp have a smaller amplitude of approximately 100 μV. The frequencies of these waves range from 0.5 to 100 Hz, and their character is highly dependent on the degree of activity of the cerebral cortex. In a normal person they can be classified as belonging to one of four wave groups: alpha, beta, theta, and delta.

Alpha waves are rhythmic waves occurring at a frequency between 8 and 13 Hz. They are found in EEGs of almost all normal persons when they are awake in a quiet, restful state of cerebration. These waves occur most intensely in the occipital region, but can also be recorded at times from the parietal and frontal regions of the scalp. Their voltage is approximately 20–200 μV.

Beta waves normally range from 14 to 30 Hz. During intense mental activity, they can be as high as 50 Hz. These waves may be divided into two major types: beta I and beta II. The beta I waves are affected by mental activity in much the same way as the alpha waves. The beta II, on the other hand, appear during intense activation of the central nervous system or during tension.

Theta waves have frequencies of approximately 4–7 Hz. These waves occur mainly in the parietal and temporal regions of children, but they may also occur during emotional stress in some adults, particularly during times of disappointment and frustration.

Delta waves include all the waves in EEG below 3.5 Hz. Sometimes these occur only once every 2 or 3 seconds. They occur in deep sleep, in infancy, and in cases of serious organic brain disease or damage.

3.2. *AXIOMATIC GLOBAL MODELING*

Research on systematic representations of the relationships of human beings and related topics in control systems is very difficult and is still in its early stages. This is particularly true in dealing with the foundations of measurement and estimation of the variables and modeling of dynamic activities in human decision making.

The modeling approach which will be discussed in this section is based on ancient eastern medical theories, namely, the yin-yang theory, the five-element theory, and the acupuncture theory [5, 19, 22–24, 49, 55]. Many concepts arising from these theories are difficult to explain in Western terms because the eastern theories are based on a global approach, and Western theories are based on a segmented or topical approach.

However, in this study we will try to bring together these two methodologies. In so doing, the eastern theory will be used to construct a global theoretical model and the western theory to deal with questions of how to measure the human state.

Now we will concern ourselves briefly with two important hypotheses, namely the yin-yang hypothesis and the five-basic-element hypothesis.

Yin-Yang Hypothesis

Ancient oriental philosophy states that yin and yang represent the universe, which contains opposing elements of all things and all actions. This hypothesis affects every issue, and all events possess the two sides, yin and yang. Some examples are as follows:

For the environmental system the earth defines yin and the rest of the environment is yang.

For time, the day is yang and the night is yin.

For humans, the man is yang and the woman is yin.

For work, success means yang and failure yin.

For human activity, work means yang and relaxation yin.

For sex character, the male is yang the female is yin.

For the quality of life, domestic life defines yang and international relations yin.

The definition of yin and yang is flexible. For example, for human activity you can construct other definitions (work could be defined by yin and relaxation by yang), but the approach must be unique, especially concerning attributes of the event. This complex hypothesis may be crudely exemplified by using the event "white night" in Leningrad and similar areas located above 60° northern latitude. We begin with the definition of day and night. A normal definition of the day is the time when we can see the sun and cannot see the stars and moon, and of the night is the time when we cannot see the sun and can see the stars and moon. In this typology the question is the membership function of seeing the sun, which can be formally defined by $\mu_S(x)$, where S is a fuzzy restriction of seeing the sun, and x is the observation point. Similarly, we have the definition of night by $\mu_M(x)$, where M is a fuzzy restriction of seeing the moon and stars. Evidently, $\mu_S(x)$ depends on the observation point on the meridian of longitude. Another possible definition of day and night is that the day begins at 6:00 A.M. and ends at 6:00 P.M., and the night begins at 6:00 P.M. and ends at 6:00 A.M. In this approach the measure of day is the membership function of the time between 6:00 A.M. and 6:00 P.M. Formally we can describe that by $\mu_D(x)$, where D is a fuzzy restriction for daytime and x is the observation point. Similarly, we have the assertion for night with $\mu_N(x)$, where N is a fuzzy restriction for nighttime. Obviously, the value of $\mu_N(x)$ and $\mu_D(x)$ change with the time, but not with the observation point on the meridian. Using the abovementioned concepts the "white night" in Leningrad may be defined by following combination:

$$\text{white night} := (\mu_N(x), \mu_S(x)), \tag{3.1}$$

where x is the observation point, Leningrad.

If you take a collection of observations on $\mu_S(x)$ and $\mu_M(x)$ along the 30°-east meridian from southern Sudan to Leningrad in the USSR at the time of white night, you get the graphical representation in Figure 6, from which you can see the $\mu_S(x)$ reduces to a minimal value, ϵ, around 12:00 P.M., where day defined by $\mu_S(x)$ goes into night defined by $\mu_N(x)$.

In view of this explanation, we can see that the more points of view one has of an event, the more complete are the assertions one can obtain, and the better decision one can make. Using these considerations the hypotheses on yin and yang may be explained as follows.

HYPOTHESIS 1. Every aspect of life contains elements of yin and yang. Both are important for the existence of life. If the balance between yin and yang is upset, then disharmony in the form of illness, chaos, or failure is possible. Therefore one must maintain the balance between yin and yang if life and harmony are to continue. If there is no day, then there is no night; without males, there can be no females (and vice versa).

In this context Albert Einstein has written an amusing equation $X = A + B + C$, to explain that success in life is to know how to work (A), how to relax (B), and how to have a harmonious community (C). It seems that different scientific approaches sometimes have the same background.

HYPOTHESIS 2. In yang there exist elements of yin and vice versa. Nothing can exist entirely as yin or yang, but all things must contain elements of both, the balance between the two representing life and continuity. Symbolically, we can make a graphic representation of the yin-yang construction in Figure 7.

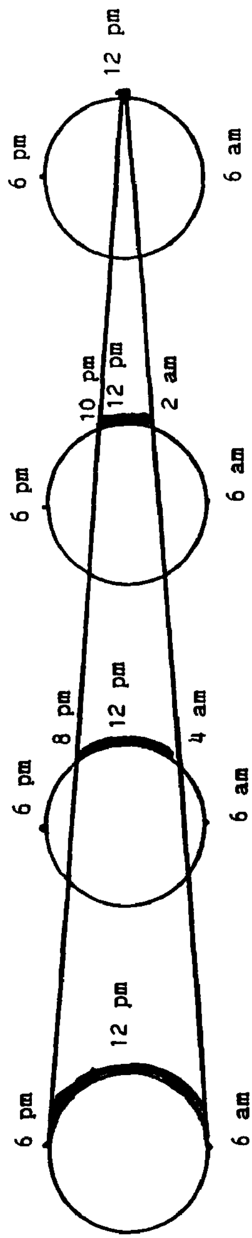


Fig. 6. Representation of day and night times at 30° longitude from southern Sudan to Leningrad, USSR.

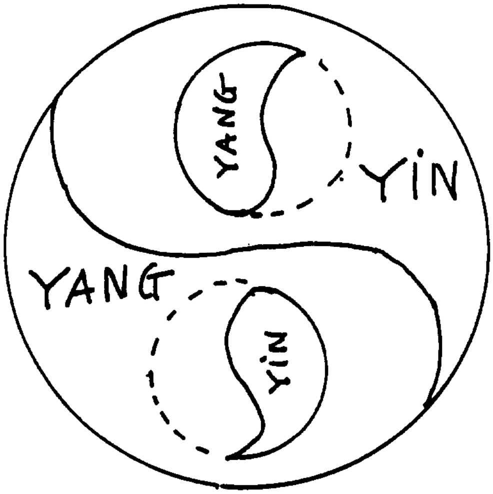


Fig. 7. Schematic representation of the yin-yang hypothesis.

Hypothesis of the Five Elements

Ancient philosophers in Asia observed that the evolution of nature may be viewed as composed of five elements, namely, wood, fire, earth, metal, and water. This hypothesis results from general observations of fundamental rules in nature. One sees that wood is necessary to have a fire that results in ashes, which are earth; from earth comes metal, and from metal one has water; from water comes wood, and the circle is completed. This observation is the basis for formulating the hypothesis of the five elements, which can be used for defining the character of an issue, the constitution of nature, the color of an event, and so on. Some examples of these terms are furnished as follows: Representation of the five stages of an abstract evolutionary process contain the beginning stage, the development stage, the surgery stage, the deterioration stage, and the destruction stage. A mathematical formulation of this assertion may be furnished by an exponential equation as follows:

$$\mathcal{G} := e^{axt}. \tag{3.2}$$

The colors are defined as yellow, green, blue, orange, red. A mathematical description of this definition may be given by a multivalued estimation as

$$\mathcal{G} := \{0.00, 0.24, 0.50, 0.75, 1.00\}. \tag{3.3}$$

The assertion of satisfaction is in grades as "very bad," "bad," "moderate," "good," "very good." This may be formulated by an exponential equation, which is easy to calculate in simulation. For the assertions "very bad" and "bad" we use

$$\mathcal{G} := 1 - \{\exp[a_s \operatorname{abs}(x - x_i)]\}^{-1}, \tag{3.4}$$

where a_s is called the interactive coefficient and is defined by the decisionmaker for "very bad" and "bad," respectively. For the assertion "moderate" we use

$$\mathcal{G} := \left\{\exp\left[b(x - x_i)^2\right]\right\}^{-1}. \tag{3.5}$$

For the assertions "good" and "very good" we use

$$\mathcal{G} := 1 - \left\{\exp\left[c_g(x - x_i)\right]\right\}^{-1}, \tag{3.6}$$

where c_g should be defined by a decisionmaker.

The rule governing the activity of the five elements can be explained by the impact-destroy rule, which requires a bit of explanation. The impact rule can be represented as a cycle {wood-fire-earth-metal-water-wood} in which each element has a creative interaction with the succeeding element. Similarly, the destroy rule can also be represented by a cycle {wood-earth-water-fire-metal-tree} in which each element has a destructive interaction with the succeeding element. Combining these aspects, we obtain the impact-destroy rule shown in Figure 8.

HYPOTHESIS 3. All events and issues of nature derive from the five elements. Their activity and function depend on the impact-destroy rule, and these guarantee the stability and development of all things.

Ancient oriental medical theory assumed that the human state depended on the condition of 12 organs (lung, large intestine, stomach, spleen, heart, small intestine, urinary bladder, kidney, gall bladder, liver, pericardium of the heart, triple warmer), and two vessels traditionally identified as the governing and conception vessels. Each organ is associated with one of the five elements. The 12 organs are associated with meridian points (Figure 9).

In describing this problem in cybernetic terms, for impact we use the term feedforward control, and for destroy, feedback control. In so doing the impact-destroy rule is replaced by the feedforward-feedback control rule, which is represented in Figure 10 below. The reader can recognize the similarity of

Figure 10a and Figure 10b. Figure 10a shows the typical interpretation in terms of machines, as in nuclear-reactor control or electrical-generator control. Figure 10b shows the feedforward regulation of the lung by the heart and its feedback regulation by the spleen. Obviously, this relation is nonlinear, and its measurement and calculation are difficult. Unfortunately, this approach has yet to be developed.

Nevertheless, our study should be continued, because a huge number of practical medical successes are witness to the validity of the theory. We can now use this methodology for a global explanation of the human-dynamics model based on the feedforward-feedback control rule with respect to the relation of all organs of the human body with regard to impact-destroy activity. Formulation of this system in graphic form then gives us the original graph $G(V, A)$, where V is the set of vertices and A is the set of arcs.

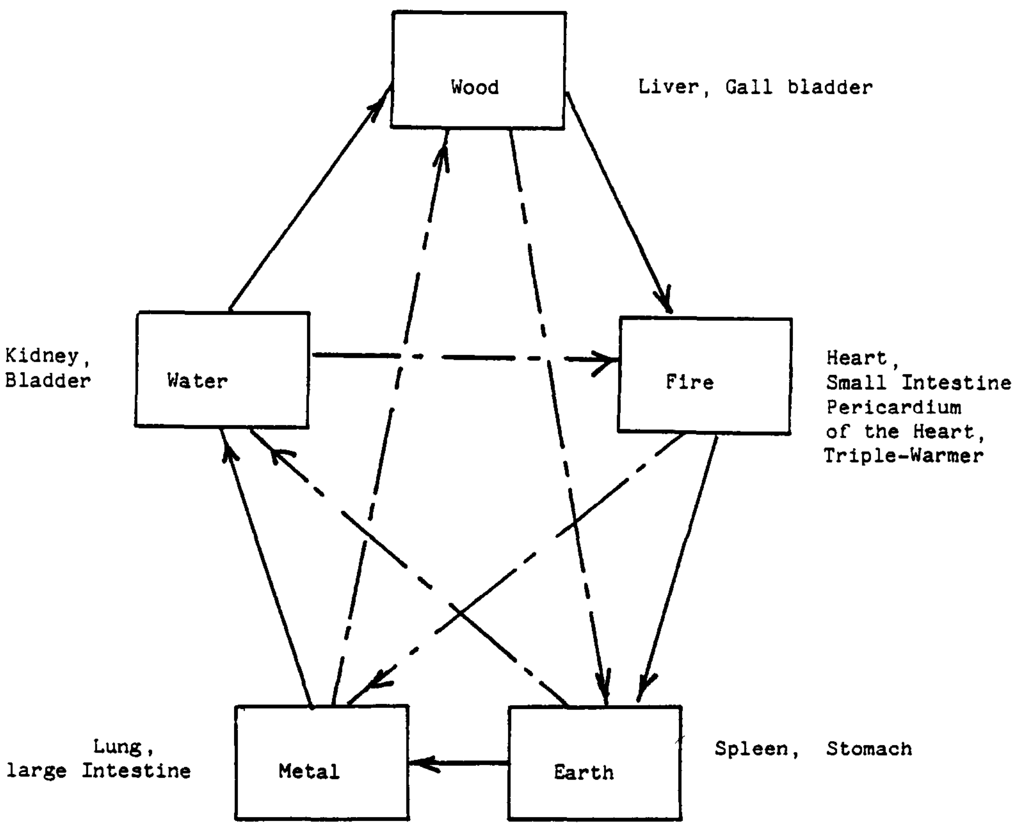


Fig. 8. Structure of the five elements and their relationships.

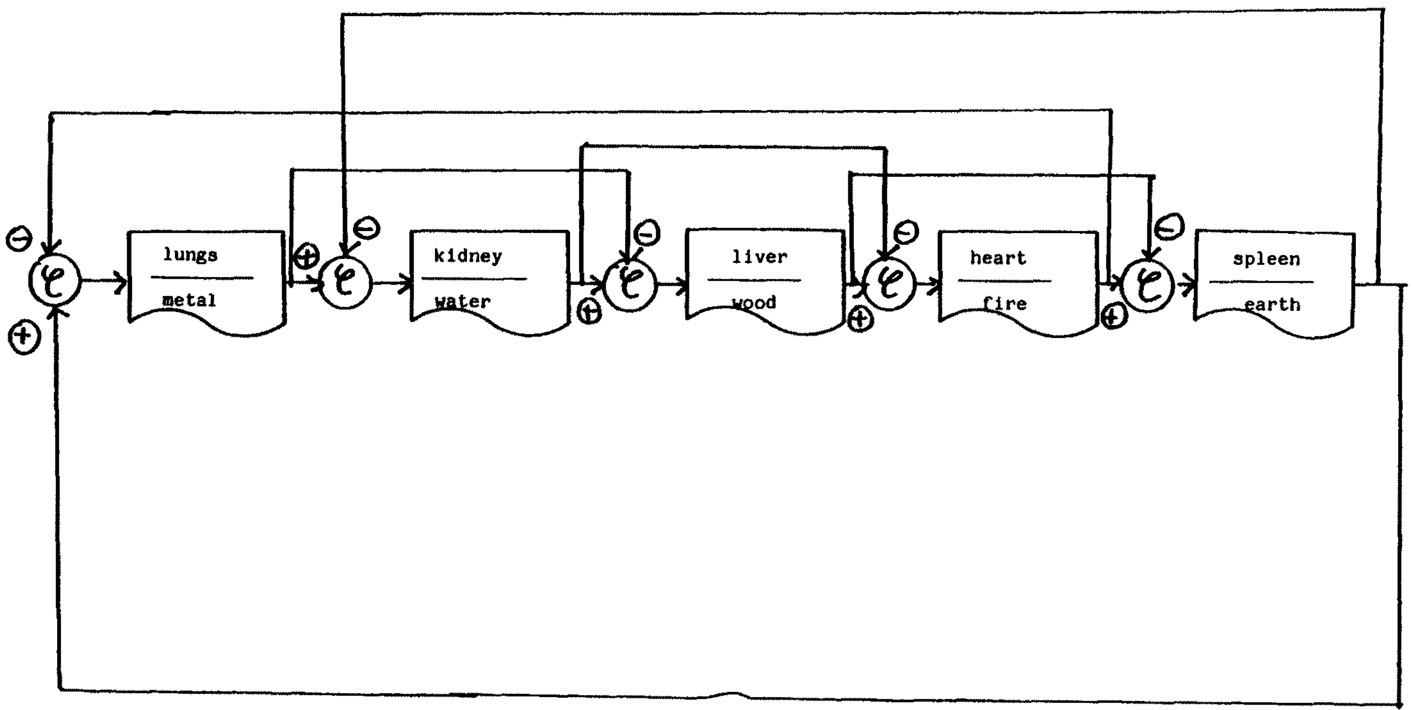


Fig. 9. Global representation of human dynamics.

To complete $G(V, A)$ one must use measurements such as temperature or electropotential measurements. If the state of each vertex is measurable, then we can obtain a measurement graph $M(N, L)$, where N denotes nodes and L lines. Assume the graph M can be completed by measurement data, which are calculated by Equation (2.6) or by Table 1.

Formally, we can construct a simulation of the human being as follows:

$$\mathcal{G} = (\mu_{AB}, \mu_{AC}; \mu_{BC}, \mu_{BD}; \mu_{CD}, \mu_{CE}; \mu_{DE}, \mu_{DF}; \mu_{EF}, \mu_{EG}), \tag{3.7}$$

where A, B, C, D, E depend on the choice of impact circle, F identifies A, and G identifies B. A circle can start with A and F representing water, B and G representing wood, C representing fire, D representing earth, and E representing metal. In general, two kinds of experiments are used in this field—temperature measurement and electropotential measurement. For measuring temperature Equation (2.6) will be used to determine the power of the vertex, that is, the organ state. For electropotential measures either Equation (2.6) or the equation system shown in Table 1 may be used.

It is worth noting that, when using western methods, the measurement of biomedical quantities is achieved through the application of fuzzy measures and possibility distributions. Now we will give some examples. For instance, in a normal person a body temperature of 36.5 to 37.0°C indicates a normal, healthy state. An expression of this event in fuzziness is given in [18]:

$$\mu_T(h) = \left\{\exp\left[\alpha_3(x - x_i)^2\right]\right\}^{-1} := \text{normal}, \tag{3.8}$$

where T is the fuzzy margin of temperature, and h is the experimental human subject. Intense mental activity is characterized by a wave which has a frequency of approximately 14–30 Hz. Similarly, in the case of temperature, high mental activity is ambiguously defined in the area 14–30 Hz. In other words, we have the fuzzy measurement

$$\mu_M(h) = 1 - \{\exp[\alpha_4(x - x_i)]\}^{-1}. \tag{3.9}$$

From the publications [22, 23, 25, 26, 28, 39, 40] you may be aware that an important source of difficulty in developing mathematical models for biology has been that we have been trying to use standard, conventional calculus, a mathematical system developed for physics and conventional engineering, which is in many cases inappropriate for biology. Therefore, it is necessary to develop mathematical and systematical tools that are appropriate for biological study. For this purpose, a tentative constructive method based on fuzzy set and possibility theory for modeling and measuring of human beings will be provided.

As was mentioned earlier, the biovariables are often uncertain and ambiguous in character. Therefore, it is necessary to elaborate a signal estimation method for obtaining reliable and confident information. This program will be carried out by introducing robust estimation.

Now let us return to the question of modeling. Let x be a variable which takes values in a universe of discourse U; here U comprises all acupuncture points. Let the generic element of U denoted by u, and $x = u$ signify that x is assigned the value $u \in U$. Let variables $x_1, \ldots, x_n$ take values in $U_1, \ldots, U_n$, respectively, which are constrained by a system of fuzzy constraints $F_1, \ldots, F_n$. Then denote by π the possibility distribution of x, that is, the fuzzy set of possible values which x can take in $U = U_1 \times \cdots \times U_n$. More explicitly,

$$\pi_x(u) = \mu_F(u) := \text{Poss}(x = u). \tag{3.10}$$

When the event being considered consists of a finite collection of statements $\{S_1, \ldots, S_N\}$, let

$$\pi^{S_j}(x_1, \ldots, x_N) \tag{3.11}$$

denote the possibility distribution induced by $\{S_j | j = 1, \ldots, N\}$ and assume that S_j are independent. Then the estimation of the event should be defined as the global possibility distribution which may be represented as

$$\pi(x_1, \ldots, x_N) = \pi^1(x_1, \ldots, x_N) \wedge \cdots \wedge \pi^N(x_1, \ldots, x_N), \tag{3.12}$$

where $\wedge$ denotes the min operator, so that

$$\pi_{(x_1, \ldots, x_N)}(u_1, \ldots, u_N) := \text{Poss}(x_1 = u_1, \ldots, x_N = u_N), \qquad u_i \in U_i, \quad i = 1, \ldots, N. \tag{3.13}$$

If we are interested in the possible values of a variable x_i, indicated by $\{x_{i1}, \ldots, x_{ik}\}$, that means we must find the local possibility distribution $\pi(x_{i1}, \ldots, x_{ik})$ from the global possibility distribution $\pi(X_1, \ldots, X_N)$. Using the result of Zadeh in [54], the desired possibility distribution is defined by the projection of $\pi(X_1, \ldots, X_N)$ on $U_{i1} \times \cdots \times U_{ik}$.

Formally, we can write this as $U_{i1} \times \cdots \times U_{ik}\pi(X_1, \ldots, X_N) :=$ [projection on $U_{i1} \times \cdots \times U_{ik}$ of $\pi(X_1, \ldots, X_N)$]. For convenience, let $X(s) = (x_{i1}, \ldots, x_{ik})$ denote the subvariable of the variable $X = (X_1, \ldots, X_N)$. Let $\pi X(s)$ be a projection of the global possibility distribution $\pi(X)$ on the corresponding $U(s) := U_{i1} \times \cdots \times U_{ik}$. Thus we obtain

$$\pi_{X(s)} u(s) = \sup_{u(s)} \pi_X(u). \tag{3.14}$$

Combining Equations (3.12), (3.14) we obtain the expression for the estimation, $E(\cdot)$, of measured values as

$$E(X_i | X) = \sup\inf \pi^{s^j}(X_1, \ldots, X_N). \tag{3.15}$$

Global Model of Human Beings

There has been a large amount of successful research on individual processes at each level of the system shown in Figure 10, and the field is growing rapidly [25, 26]. But the task of determining how these processes interact to constitute a human's dynamic system, which may have a global character, is only now beginning [22, 28]. As was mentioned earlier, this question is very important in considering man-machine systems because we have to deal with human ergonomics under the influence of different factors such as biochemical state, physiological response, etc.

Of particular interest are questions of quantitative assertion of psychological and cognitive behavior of the human operator/decisionmaker with respect to the influence of his biochemical and physiological state variables on his working and living conditions. The character of the problem considered is typically uncertain and ambiguous. Therefore, some unconventional and non-

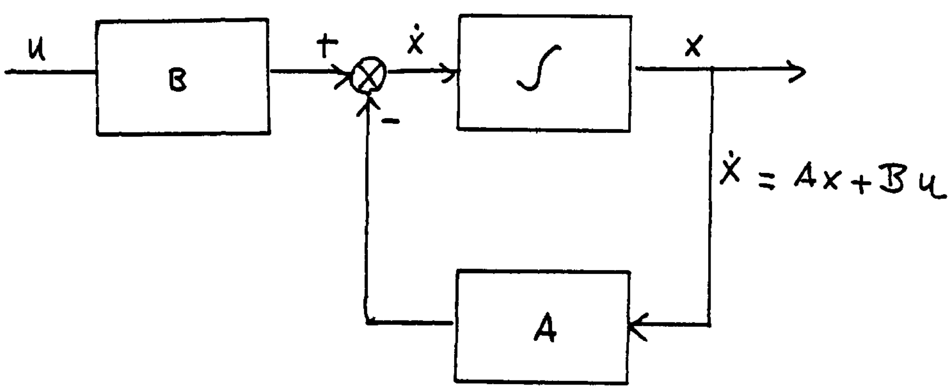


Fig. 10a. Conventional feedforward-feedback control.

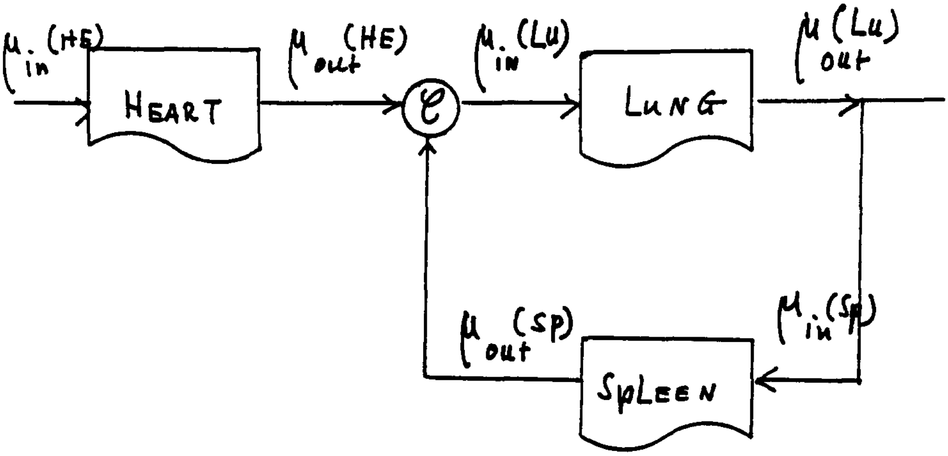


Fig. 10b. Nonconventional feedforward-feedback control.

standard theories, such as fuzzy set and possibility theory and robust statistics, can help in the delineation of these matters. In this section we shall deal with a fuzziness approach for constructive modeling of human dynamics and related cognition processes.

Under the stated assumptions we begin the study in this section with the question of the formal connection of the four main vital levels shown in Figure 4. As was mentioned earlier, the relationships between these vital processes are very complex, and pure analytical expression seems extremely difficult. To overcome this obstacle, our basic idea underlying the joint generating function is to use data analysis and conglomeration methods which are based upon fuzzy set and possibility theory.

Basically, adopting the useful idea of age-dependent branching processes given in [56], the relations from the genetic level to the psychological level may principally be formulated as follows: for the genetic level

$$F_4(s_4, t_4); \tag{3.16}$$

for the biochemical level

$$F_3(s_3, F(s_4, t_4), t_3); \tag{3.17}$$

for the physiological level

$$F_2(s_2, F_3(s_3, F(s_4, t_4), t_3), t_2); \tag{3.18}$$

for the psychological level

$$F_1(s_1, F_2(s_2, F_3(s_3, F_4(s_4, t_4), t_3), t_2), t_1), \tag{3.19}$$

where s is the state of each individual level, which can be obtained by the measures discussed in Section 3.1, at a given time. For simplicity we assume that the observed time t represents all individual times, and $F_1, \ldots, F_4$ are formal transformation functions. The approach to projection of the possibility distribution given in (3.13) will be used to formulate concrete calculations.

Now let us consider in detail the dynamics at the physiological level (using electropotential sensory measures) or at the biochemical level (using thermometric sensory measures). The problem can be stated with the notation for the continued sampling associated with a sequence $\{x_i | i = 1, \ldots, M\}$. Let $N(t)$, or N for short, be the number of measurements at time t in an independent vital process with genetic function $f(g)$ and distributive time denoted by $t(d)$, or t for short. Assume that the possible strength of the measured state variable may be expressed as

$$\mu(x_i) = \int_0^{\infty} f(g)\, dt < \infty \tag{3.20}$$

and its values are discrete and measurable. For convenience of calculation, suppose that the highest activity of genetic function can be expressed by $\mu(f(g)) = 1$, and the lowest activity by $\mu(f(g)) = 0$; then we can obtain the definable space of measurements as

$$\mu(x_i) = [0,1]. \tag{3.21}$$

Basically, the problem is considered using a fuzzy-set-theory approach. Assume a measurable space defined by a triple $(U, \mathscr{A}, M)$, where $\mathscr{A}$ is a family of functions on the set U, and M is a family of functions on $\mathscr{A}$ such that for every μ in M, the triple $(U, \mathscr{A}, \mu)$ is a fuzzy measure space [13]. For any simple measurable positive function,

$$\mu = \frac{1}{N} \sum_{i=1}^{N} \alpha_i \mu_A(x_i) \qquad \text{for all} \quad A \in \mathscr{A} \tag{3.22}$$

as a power of the considered fuzzy set, where N is the number of measures, and α_i is the judgment coefficient in accordance with a learning process. Therefore, the power μ in Equation (2.6) can be used to represent the state s in Equations (3.16)–(3.19).

The estimation of α is very important, because it is a criterion for determining success or failure. One of the most simple but efficient methods to calculate α is the determination of the weight function of the Hamming distance [13]. For instance, assume the problem considered possesses N classes (situations or experimental conditions) and M attributes for each class. Therefore, the weight function may be roughly expressed by

$$\alpha_i = \sum_{i,j} \gamma_j \delta_{ij} + \epsilon_i, \qquad i \in N, \quad j \in M, \tag{3.23}$$

where α_i is the overall distance of class i from the "ideal" class, δ_{ij} is the distance of the ith class from the "ideal" point on attribute j, γ_j is the weight of attribute j, and ϵ_i is an error term. For simplification let γ_j take the value 1.

Assume in the paired preference comparison an individual decisionmaker or human operator prefers class l over class k. We obtain

$$\begin{aligned} \Delta\alpha_{kl} &= \alpha_k - \alpha_l \\ &= \sum_{j=1,\ldots,M} \gamma_j(\delta_{kj} - \delta_{lj}) + \epsilon_{kl} \geqslant 0. \end{aligned} \tag{3.24}$$

The difference $\Delta\alpha_{kl}$ may be recognized in the fuzzy linguistic assertion

$$\Delta\alpha := L = \{ L_1|\text{very small}, L_2|\text{small}, L_3|\text{moderate}, L_4|\text{large}, L_5|\text{very large}\}. \tag{3.25}$$

The weight coefficient, ideal class, and ideal point have been determined by a decisionmaker. Therefore research, learning, and training on human being and human decisionmaking plays an important role in modern man-machine systems control.

By the results just mentioned above, Equations (3.16)–(3.19) can be evaluated. Now the question of conglomeration from level to level by conditional possibility will be considered.

A possibility measure on a fuzzy algebra $\mathscr{A}$ with unit $\mathscr{U}$ is a finitely fuzzy-additive, nonnegative function normalized so as to assume the value 1 on $\mathscr{U}$. Furthermore, if $\mathscr{V}$ is subalgebra of a fuzzy algebra $\mathscr{F}$, then π is a conditional possibility on $(\mathscr{F},\mathscr{V})$, and the triple $(\mathscr{F},\mathscr{V},\pi)$ is a conditional possibility space. In other words, $\mathscr{F}$ denotes consideration space of all events, and $\mathscr{V}$ denotes the events at a certain individual level. If π is a function, its value is $(\mathscr{F}, \mathscr{V}^0)$, $\mathscr{V}^0 := \mathscr{V} \setminus \phi$, satisfying

$$\pi(\cdot\,|v) \text{ is a possibility measure on } \mathscr{F} \text{ for each } v \in \mathscr{V}^0, \tag{3.26}$$

$$\pi(v|v) = 1 \qquad \text{for all} \quad v \in \mathscr{V}^0, \tag{3.27}$$

$$\pi(A|C) = \pi(A|B)\pi(B|C), \qquad A \subset B \subset C, \quad A \in \mathscr{F}, \quad B, C \in \mathscr{V}^0. \tag{3.28}$$

A conditional possibility π on $(\mathscr{F}, \mathscr{V})$ is full on $\mathscr{F}$ if $\mathscr{V} \subset \mathscr{F}$.

With this fact in mind, we can introduce the following propositions for conglomeration.

PROPOSITION 1. *For every conditional possibility space* $(\mathscr{F}, \mathscr{V}, \pi)$, *there is an extension* $\mathscr{T}$ *on* π *that is a full conditional possibility on* $\mathscr{F}$.

PROPOSITION 2. *Let* $\mathscr{F}, \mathscr{G}, \mathscr{V}$ *be fuzzy algebras with* $\mathscr{V} \subset \mathscr{G} \subset \mathscr{F}$, *and let* π *be a conditional possibility on* $(\mathscr{G}, \mathscr{V})$. *Then there exists a full conditional possibility on* $\mathscr{F}$ *which is an extension of* π.

PROPOSITION 3. *For each strategy* β *on* $(\mathscr{F}, \gamma)$, *there is a full conditional possibility on* $\mathscr{F}$ *which is an extension of* β, *and* γ *is a set of nonempty, disjoint subsets of* U, *whose union is* U.

4. APPLICATION SIMULATION

To explain the simulation methods, two typical problems concerned with the human factor in man-machine systems will be introduced, namely, an estimation model for human states and an analysis of man-computer interactive decisionmaking. We begin with the estimation model for human states, which is relatively simple but is an important foundation in the construction of man-machine systems, such as in the observation of an airplane pilot, or in making a diagnosis consultation system for medical application.

4.1. ESTIMATION MODEL FOR HUMAN STATES

The estimation model for human states that is discussed in this section has the aim of constructing a method for observing the human state. As was mentioned above, this is necessary for the construction of a man-machine system, or for the estimation of the state of an airplane pilot, or for observing the status of a decision-maker in a difficult and complex problem, or for building a software system for computer-aided consultation in medicine.

Assume that the problem considered may be described by a set of characters (symptoms) denoted by X, and a set of human states denoted by S. The relationship between X and S may be represented by a matrix C, called a constructive matrix, which is defined by

$$C = \{ c_{ij};\ i=1,\ldots,N,\ j=1,\ldots,M \}, \tag{4.1}$$

where N is the number of characters (symptoms) and M is the number of human states (defined conditions). To set up the constructive matrix it is necessary to use expert knowledge on western and/or eastern medicine in order to make the numerical measurements. Here temperature measurements and/or electropotential measurements on the human body will be used. These techniques are acceptable both in terms of cost (equipment cost) and effectiveness (reliability of measurement). Assuming that the matrix C will consist of temperature measurements, then we have a measurement matrix of C which is defined as follows:

$$M = \{ m_{ij};\ i=1,\ldots,N,\ j=1,\ldots,M \}. \tag{4.2}$$

The value of the element m_{ij} will be calculated by

$$m_{ij} = \sum m_{ijk}, \qquad k=1,\ldots,K, \tag{4.3}$$

where K is the number of measurements for each element m_{ij}. If we want to express the measurement in unit space, then Equation (4.3) has a new form

$$m_{ij} = \frac{1}{K} \sum m_{ij}, \qquad k=1,\ldots,K. \tag{4.4}$$

If we have a set of defined conditions, then we can build a software system for its graphic representation which is shown in Figure 11. An interesting question is the stability of the pattern. For this problem the so-called ϵ-stable matrix from [13] is introduced.

We define the product of two matrices M_1 and M_2 by

$$M^2 = M_1 \otimes M_2^T, \tag{4.5}$$

$$M^2 = \{ m_{ij}^2 \} = \min\max(m_{ij}, m_{ij}^T), \tag{4.6}$$

$$M^{n+1} = M^n \otimes M. \tag{4.7}$$

A stable, or ϵ-stable, matrix is obtained if and only if

$$M^{n+1} = M^n, \qquad \text{or} \quad M^{n+1} = M^n + \epsilon, \tag{4.8}$$

respectively, where ϵ is some small positive number. Obviously,

$$M^n \subset M^{n-1} \subset \cdots \subset M. \tag{4.9}$$

A use of this method is for example the estimation of a human state. Assume we must estimate the state of an airplane pilot. Then it is necessary to search a corresponding pattern for the considered state. In this search man-computer interactive work is necessary because expert knowledge plays an important role. The better the automated model of knowledge representation, the easier it is to search the pattern, and the more reliable the results are. But each expert must give initial values.

A measurement procedure for a pattern on the human body should deliver measurements in the form of a matrix. We compare this matrix with the pattern by means of

$$M = M^P \otimes M^O, \tag{4.10}$$

where M^P is a pattern matrix and M^O is the measurement matrix of an object. If $M = M^P + \epsilon$, then we say the human state is identified with the pattern P. If the condition (4.10) cannot be fulfilled, then we have to return to the beginning to determine a new pattern. One example, based on eastern medicinal methodology, is to measure the relationship of the three organs (lung, heart, spleen) by using a computerized experiment as shown in Figure 11.

4.2. *MAN-COMPUTER INTERACTION IN DECISION ANALYSIS*

Currently, man-computer interaction decisionmaking has been applied in many areas of science and technology: computer-based control systems for aircraft control and for exploration in space; in submarines and deepsea exploration; for flexible manufacturing operations in large-scale systems, such as electric power systems, chemical production, and biotechnological production; and so on. A typical structure of such systems is shown in Figure 12.

In these systems the decisionmaker/operator must often face difficult situations in information perception, decision simulation, etc. Such situations can be observed to involve the following problems: elaboration of the method for the human information reception from video display terminals and other voice information; understanding the role of decision making in complex systems,

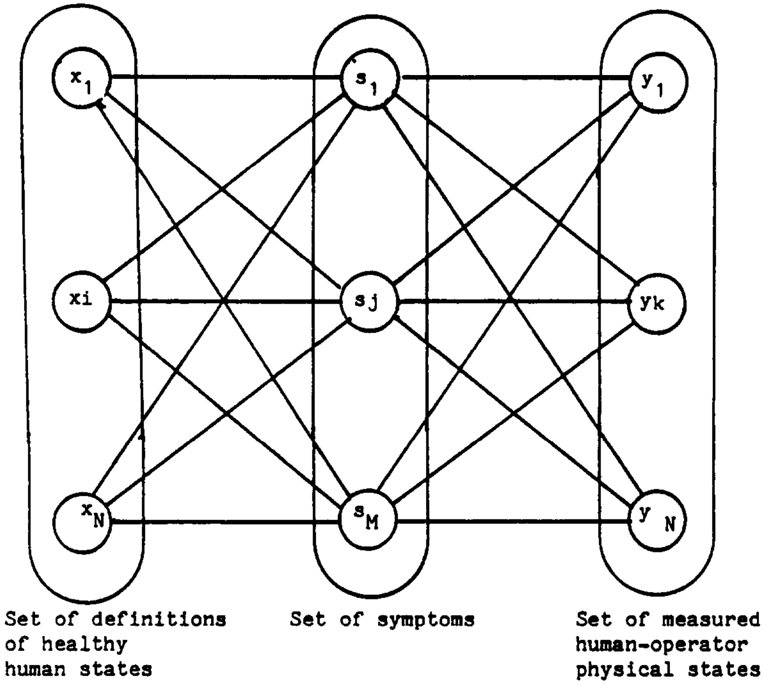


Fig. 11. Graphic representation of estimation model.

particularly of decision with delay; understanding the various sets of constraints under which policymakers, decisionmakers, and system analysts operate; communication between policymakers and decisionmakers; elaboration of a general and standard method for the evaluation of environmental influences on decisionmakers. From the viewpoint of man-computer decisionmaking these will be discussed in connection with two problems, namely, the question of incomplete and imprecise information and the question of multicriterion decisionmaking.

Incomplete and Imprecise Information

There are many methods for dealing with this problem, e.g., the Bayesian method used in [12]. In such a study the subjective probability distributions for systems are improved by statistical observations. In practice, there are cases, such as long-range prediction and planning, or biomedical diagnosis and treatment, where we do not know the relative density to describe the distribution of unreliable processes, and we cannot plan the statistical observations. In such cases fuzzy set and possibility theory seems the most suitable tool. Imprecise information about technological processes may be improved by

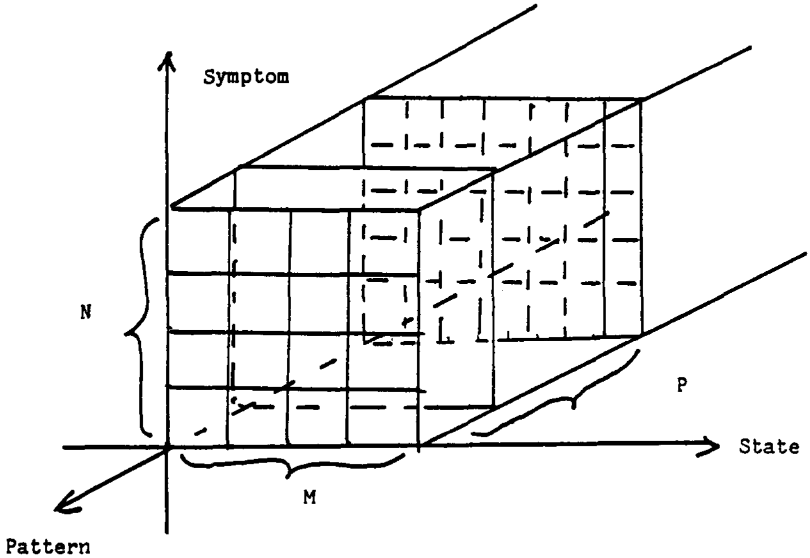


Fig. 12. Representation of the relationship between symptoms, healthy state, and observed human-operator state.

developing a stable measurement matrix [13]. For example, the data of the problem would be given in form of a matrix as follows:

$$M = M_{PQ}, \tag{4.11}$$

where P is the number of variables and Q is the number of patterns. Therefore a stable or ϵ-stable matrix to express reliable information on the process is

$$M^{n+1} = M^n + \epsilon \tag{4.12}$$

with $M^n = M^{n-1} \otimes M$.

The main intention in this section is to formulate the imprecise nature of information arising from humans. For this purpose there are some questions to deal with. The human usually receives information in man-computer interaction systems from video display terminals, from direct measuring instruments, or from audio equipment. The quality of information received depends on the quality of information from the instruments and on the human operator's state with respect to his environment. To avoid possible information failures, a robust estimation method will be introduced such that the information will become more reliable.

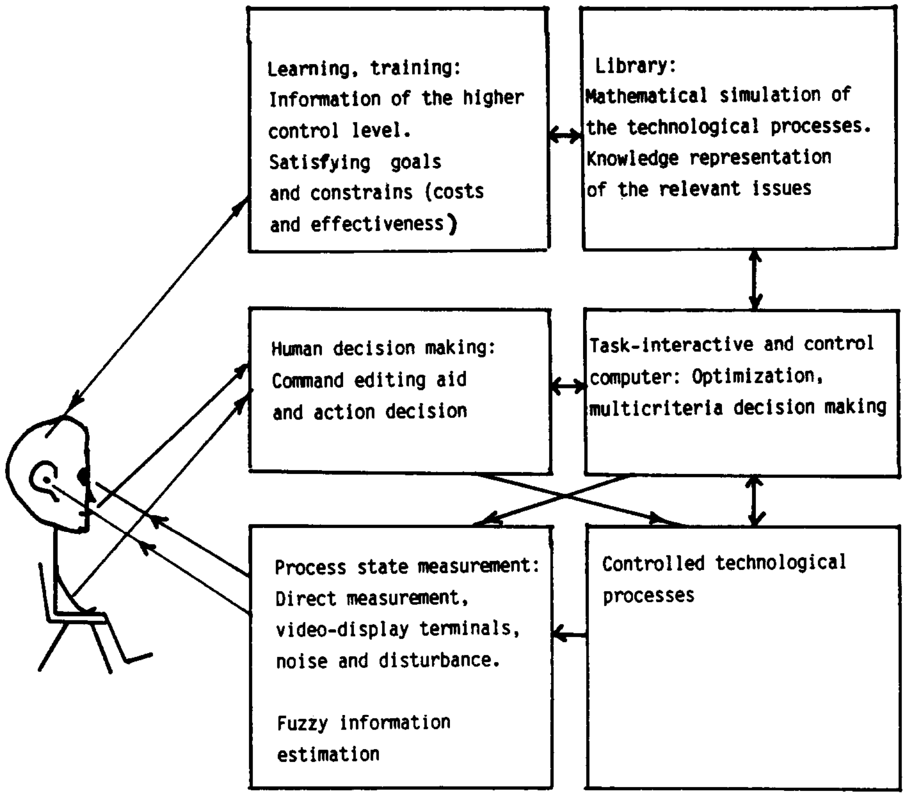


Fig. 13. Typical representation of a man-machine control system.

Human Decision Making

The general structure of man-computer interaction control is shown in Figure 13, which informs us that human decision making is necessary in this system, especially with regard to the problem of aggregated control. Obviously, there are many technical and economic problems to discuss in aggregated control. Two important problems of concern are multicriterion decision making and interaction control. Using a mathematical optimization method one can obtain the computed resolutions. For human decision making a multicriterion decision problem can be formulated by:

a set of alternatives	$A = \{a_i \mid i = 1, \ldots, N\}$,
a set of costs	$C = \{c_j \mid j = 1, \ldots, Q\}$,
a set of effectiveness	$E = \{e_k \mid k = 1, \ldots, P\}$.

We denote by A the universal set that contains all elements of relevant alternatives, by C the universal set which contains all elements of relevant costs, and by E the universal set that contains all relevant effectivenesses. For human decisionmaking analysis it is convenient to build a mapping to transform the computed solutions into a unified decisionmaking space. In so doing the fuzzy relation between alternative and cost can be defined by a set of ordered values

$$\mu(c,a): C \times A \to [0,1]. \tag{4.13}$$

Similarly, let the fuzzy relations between effectiveness and alternatives be defined by

$$\mu(a,e): A \times E \to [0,1]. \tag{4.14}$$

For this study we must begin with the following axiom: An optimal decision is defined by the maximization of the fuzzy measurements

$$\mu(c,a) \quad \text{and} \quad \mu(e,a). \tag{4.15}$$

Formally, we can describe this as follows:

$$\mu(D) = \max\left(\sum \mu(c,a) + \sum \mu(e,a)\right). \tag{4.16}$$

For simplifying the calculation and the interaction between man and computer, the costs can be constrained by the operand $\leqslant$ with the statement: the costs C must not be above the aspiration level l_a or above the highest level l_b. Assume that the fuzzy measure is linear. Based on this fact one can define the fuzzy measure for costs:

$$\mu(c,a) = \begin{cases} 1 & \text{if} \quad c \leqslant l_a, \\ \dfrac{l_a - c}{l_b - l_a} & \text{if} \quad l_a \leqslant c \leqslant l_c, \\ 0 & \text{if} \quad c \geqslant l_b. \end{cases} \tag{4.17}$$

Assume the effectiveness can be constrained by the operand $\geqslant$ with the statement: The effectiveness must not be below the aspiration level l_c or below the lowest level l_d. Motivated by the fact that the fuzzy measure is linear, we introduce the following fuzzy measure:

$$\mu(e,a)=\begin{cases}1 & \text{if} \quad e \geqslant l_c,\\ \dfrac{e-l_d}{l_c-l_d} & \text{if} \quad l_d \leqslant e \leqslant l_c,\\ 0 & \text{if} \quad e \leqslant l_d,\end{cases} \tag{4.18}$$

where all limits l_a, l_b, l_c, l_d are fixed by the decisionmaker at the time of interaction. Formally we can take for $i = a, b, c, d$

l_i := (professional knowledge, psychological state, physiological state, environmental situation, information from a policymaker).

The number of factors l_i depends on the level of importance of the problem. The more important the problem, the larger will be the number of factors. The success or failure of decisions using man-computer interaction essentially depends on the choice of l_i. Therefore it will be discussed in greater detail. We shall now discuss some important variables of this kind.

Professional Knowledge

When we consider the variable "professional knowledge," we face some of the following concerns: A human operator at a nuclear reactor may be hired only on the basis of his personal knowledge of physics. For a medical doctor professional knowledge is defined by his/her medical knowledge. In addition the doctor has to know the mental state of the patient with respect tò his life and environmental conditions, etc. For a decisionmaker in economic development planning or in company production the variable "professional knowledge" may include a set of competences such as domestic welfare, international relations, national and company authority, psychology and culture, etc. Obviously, the knowledge of the decisionmaker may be improved through learning, training, or appropriate computer-aided consultation.

Psychological State

There are a large number of variables to estimate in the psychological state of a decisionmaker. The first of these is the capacity of the human to perform information processing under stressful conditions, in an isolated situation (such

TABLE 2

Possible Quality of Cooperation between a Policymaker and a Decisionmaker

Decisionmaker's estimation	Policymaker's estimation:	*a*	*b*	*c*	*d*	*e*
a		*a*	*a*	*a*	*a*	*a*
b		*a*	*b*	*b*	*b*	*b*
c		*a*	*b*	*c*	*c*	*c*
d		*a*	*b*	*c*	*d*	*d*
e		*a*	*b*	*c*	*d*	*e*

as in space and deep-sea exploration), or in a difficult environment (high humidity, high temperature, desert conditions), and the enjoyment the decisionmaker derives from considering the problem.

Information from Policymakers

As was alluded to earlier, the most difficult problem is the information interaction between policymaker and decisionmaker, because they may have a unified goal but each has his own concrete conditions and ergonomics. In this case it seems that fuzzy language {very bad, bad, medium, good, very good} is suitable for estimation of their interaction. Assume that the authority in the cooperation between policymaker and decisionmaker is equal. Using the algebraic-product operand in Equation (2.20) for fuzzy representation $\{a := \text{very bad}, b := \text{bad}, c := \text{medium}, d := \text{good}, e := \text{very good}\}$, the results of cooperation are given in Table 2. From this cooperation table we can see that the

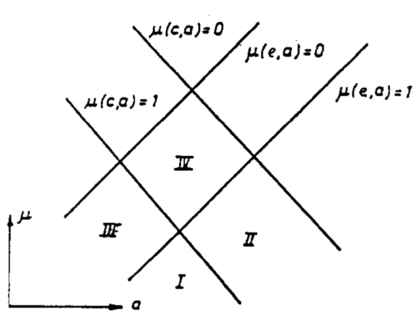


Fig. 14. Decision areas created by fuzzy measurements.

quality of decisions depends both on the decisionmaker and on the policymaker, and the best result is achieved by the string *a-b-c-d-e*. Outcomes that may be preferred by the decisionmaker but not by the policymaker do not affect the optimum.

Now we consider a simple example with two criteria representing the effectiveness e and cost c, using the groups shown in Figure 14. From the graphic display of Figure 14, the decisionmaker now has four different areas to choose decisions from, namely:

Area I, characterized by

$$\mu(e,a)=1 \quad \text{and} \quad \mu(c,a)=1. \tag{4.19}$$

In this area every point has the same value, and the decision is trivial.

Area II, characterized by

$$\mu(e,a)=1 \quad \text{and} \quad \mu(c,a)=[0,1]. \tag{4.20}$$

Area III, characterized by

$$\mu(e,a)=[0,1] \quad \text{and} \quad \mu(c,a)=1. \tag{4.21}$$

For areas II and III the decision analysis is a little more complicated. Here one can select the preferred purpose of the policymaker with regard to whether he/she will prefer the cost constraints or the effectiveness aims. If cost constraints are preferred, then the decision analysis will take place in area III. In this case a decisionmaker strives to obtain the greatest $\mu(e,a)$, in other words, to obtain maximum effectiveness. If the effectiveness aims are preferred, the decision analysis will take place in area II; then the decisionmaker strives to obtain the greatest $\mu(c,a)$, in other words, achieve minimum cost.

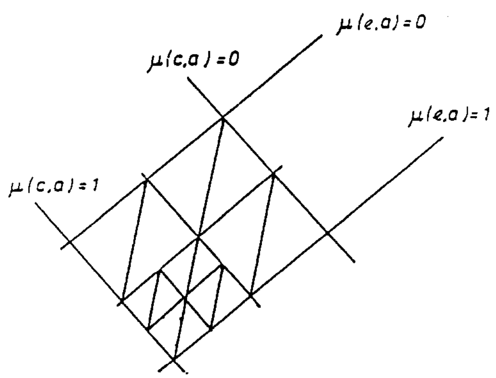


Fig. 15. Decisionmaking in nondominated areas.

Area IV, characterized by

$$\mu(e,a) = [0,1] \quad \text{and} \quad \mu(c,a) = [0,1]. \tag{4.22}$$

For decision analysis it is necessary to be concerned with professional knowledge, the psychological state of the decisionmaker, and the information of a policymaker, which has just been discussed.

Similarly to the decision analysis in areas I, II, and III, the analysis in area IV can be carried out by using corresponding subareas 1, 2, 3, and 4. The thin lines in Figure 15 show the set of appropriate decisions in different subareas of area IV.

5. CONCLUDING REMARKS

Human factors are an increasingly important issue of information science and technology, particularly for the foundations of brainware for man-machine systems and also for medical research and application.

There are interesting ideas about chemical coding in large molecules such as RNA and neural coding by altering the properties of synapses, that is, the junctions between neurons in the brain [30]. Furthermore, in the life sciences there have been two great revolutions during the last decades. One concerns gene-directed protein biosynthesis, and the other energy metabolism. These two disciplines are deeply interconnected conceptually [57]. Energy metabolism requires many proteins, and protein biosynthesis uses considerable metabolic energy. Therefore, in summary, there exist three connected areas namely, energy metabolism, protein biosynthesis, and human information processing. The bridges between them are the delivery of metabolic energy from energy metabolism to protein biosynthesis; the coding in RNA of biosynthesis related to long-term memory; and thinking and reasoning (human information processing).

Certainly, research on these bridges is characterized by great importance and extreme difficulty. In our foregoing analysis, some—but by no means all—fundamentals of the overwhelming complexity on human dynamics have been depicted: those arising in establishing the theoretical formalism of man-machine systems. This study is intended to suggest that the capacity of a human for information processing depends on his physiological state, psychological state, and cognitive faculty.

Applying representive problems of fuzzy set and system theories enables us to build explicit and well-founded models.

Introducing the theory of five elements and the yin-yang theory of oriental philosophy in model construction seems to be appropriate for global observation of human dynamics.

Not least, it is worth noting that the time is not yet ripe to form an explicit and well-founded system, but the results presented are one of the first achievements and we look forward to future developments.

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