

AN EXPERT SYSTEM WITH THINKING IN IMAGES

Zhang Hongmin

Department of Mechanical Engineering,
The Air Force College of Engineering,
Xi'an, China

Abstract

In this paper we present a new method of modelling human thinking in images, which had been applied to the expert systems for diagnosis of faults in aircraft and blood diseases. In this method, first, the knowledge and experience of experts are described by the theory of fall shadows random sets in the factors space. Secondly, to gain their knowledge and experience, we put them to the psychology test according to the theory of fall shadows statistics. Thirdly, we consider thinking in images as a process of comparing, analysis and recognition. Finally, we apply consciousness-tree to modelling the complex process.

Keywords: Expert systems, thinking in images, fall-shadows of random sets, set-valued statistics, consciousness-tree

1. INTRODUCTION

An expert system is an information processing system, which could store human knowledge and experience as model human thinking process for processing knowledge and information. So far, it has made great progress in modelling human logical thinking. Some high-level programming languages, as LISP, PROLOG and so on, which are applied to artificial intelligence, have been offered.

According to professor Gian Xieshen's points of view, however, modes of human thinking may be divided into logical thinking, thinking in images and inspirational thinking. We consider that the main study direction of artificial intelligence would be thinking in images and inspirational thinking.

Logical thinking is a process of using concepts for judgment and inference. The inference process must abide by some rules and certain program. In the real world, human experts apply logical thinking as well as thinking in images. For instance, when an engineer with abundant experience makes a decision for some problem, his thinking process is that he recognizes a matter by making use of image according to his experience. His foundation of decision-making is not some concepts and rules, but some practical matters and impressions of imagery in human brains. This is what we mean by saying thinking in images. It is very much different from logical thinking.

Generally, human recognizes matters by thinking in images from an integral impression. Thinking in images has features, that is, fuzziness and integrality. A doctor does not diagnose patient's illness according to a single symptom of temperature, blood pressure, or weight and pure reasoning rules, but according

to all the symptoms of the patient's illness and his own (or even tragedy). For this reason, we should apply some method of fuzzy mathematics for representing the process of thinking in images.

In this paper, we present a new idea and method of modelling human thinking in images, i.e., the basic theory of knowledge representation, knowledge acquisition and application of knowledge. We use the method to build up a STIM (Shell with Thinking in Images) expert system, which has been applied to the expert systems for diagnosis of faults in aircraft and blood diseases, and gained satisfactory results.

2. KNOWLEDGE REPRESENTATION

In this section, we offer a new mathematical method, which describes knowledge of thinking in images.

2.1 Factors space

Factors space would be useful for mathematically describing the real world [1]. In this paper we are going to use some theory on factors space.

DEFINITION 2.1 A factors space is a family of sets $\{X_f\}_{f \in F}$ where F is a complete Boolean algebra $F = (F, \vee, \wedge, c)$ satisfying

$$1) \quad X_{\emptyset} = \emptyset; \quad (2.1)$$

2) if $\{f_t\}_{t \in T}$ are independent, i.e., for any $t_1, t_2 \in T$, $t_1 \wedge t_2 = \emptyset$, then

$$\bigvee_{t \in T} f_t = \prod_{t \in T} X_{f_t} \quad (2.2)$$

where 0 and 1 are the smallest and the largest element of F respectively, and $\prod_{t \in T}$ is Cartesian product, allows that

$$\{\emptyset\} \times \prod_{t \in T} X_{f_t} \quad (2.3)$$

We call the elements of F the factors, X_f the range of factor f and X_1 the whole range or state space.

An image of object can be described as point in a finite or finite-dimensional factors space. In doctor's image, for instance, a patient's state may be described as a point in multidimensional factors space where the factors are sex, weight, temperature, blood pressure, etc.

For $f, g \in F$, $g \leq f \leq h$ define

$$\uparrow_f^h A \triangleq A \times X_{(h \wedge f^c)} \quad (2.4)$$

and also

$$\downarrow_g A = \{x \mid x \in X_g \ \& \ (\exists y \in X_{(f \wedge g^c)}) \ (x, y) \in A\} \quad (2.5)$$

where \uparrow_f^h is the cylindric extension of A from f to h and $\downarrow_g A$ the projection of A from f to g .

DEFINITION 2.2 For any $A \subseteq X_1$, define

$$\tau(A) \triangleq \wedge \{f \mid \uparrow_f A = A\} \quad (2.6)$$

Use $\tau(A)$ the rank of A . if $f \geq \tau(A)$, we say that A is clear in

λ_f other, we may say that A is unclear in X. If $f \leq \tau(A)$, we offer a concept of clear degree.

DEFINITION 2.3 Let δ be a function from σ -algebra to $[0,1], \forall A \in \mathcal{F}$, δ is a clear degree satisfying the conditions:

$$1. \delta_A \emptyset = 0; \delta_A(f) = 1, \quad f \geq \tau(A) \quad (2.7)$$

$$2. \text{If } h \wedge g = 0, \text{ then } \delta_A(h \vee g) = \delta_A(h) + \delta_A(g) + \lambda \delta_A(h) \delta_A(g) \quad -1 < \lambda < 1$$

$$h, g < \tau(A); \quad (2.8)$$

$$3. \text{If } \forall n \in \mathbb{N}, f_i \in \mathcal{F} \text{ and } f_i \text{ is monotonic } (f_1 \leq f_2 \leq \dots \leq f_n \leq \dots \text{ or } f_1 \geq f_2 \geq \dots \geq f_n \geq \dots), \text{ then } \lim_{i \rightarrow \infty} \delta_A(f_i) = \delta_A(\lim_{i \rightarrow \infty} f_i) \quad f_i < \tau(A) \quad (2.9)$$

The clear degree is a λ -fuzzy measure. Equiprobability of fuzziness can be described by the clear degree.

DEFINITION 2.4 Let $(X_f, \mathcal{B}_f, P_f) (f \in F)$ a factors field $(f \in F)$

$f \in F$ is a factors space; for every $f \in F (X_f, \mathcal{B}_f, P_f)$ is a

probability field; and $(f_t) (t \in T)$ are independent then $(X_{\prod_{t \in T} f_t}, \mathcal{B}_{\prod_{t \in T} f_t}, P_{\prod_{t \in T} f_t})$

is the product probability field of $(X_f, \mathcal{B}_f, P_f) (f \in T)$.

For any $\mathcal{B} \subseteq \mathcal{P}(X_f)$, if $f \leq h$, we define

$$\uparrow_h \mathcal{B} = \{h \cap C \mid C \in \mathcal{B}\} \quad (2.10)$$

If $g \leq f$, we define

$$\downarrow_g \mathcal{B} = \{g \cap C \mid C \in \mathcal{B}\} \quad (2.11)$$

We can easily prove that:

2.2 Set-valued Statistics and Fall-shadows of Random Sets

Set-valued Statistics were proposed by Wang Peizhuang [2]. The classical statistical experiments, which are familiar to us, are mainly used to measure some physical quantities, and are rarely based upon the psychological reflections of human beings. The set-valued statistics is however closely connected with the psychological process. There is a knowledge problem here. A large number of experiments in physical psychology have proved that there exists very precisely a power function law between the changes in psychological reflection quantity which is obtained by various sense organs (such as vision organ, hearing organ, taste organ, touch organ) and the changes in various physical stimulation quantities in the outside world (such as bright degree, loud degree, sweet degree, fragrant degree). This shows that a scientific psychological measurement method may objectively reflect the real world. As to those objects which cannot be measured by physical or chemical or any other measurement means, the psychological measurement is really an important quantitating method. So we may say that bringing psychological measurement into set-valued statistics is not a fault but an advantage.

Image of a kind of object for experts can be described as a subset in the factors space. A large number of images of experts are random sets in the factors space. Now we define the measurable structure and "random variable" on $\mathcal{P}(U)$. Denote

$$\hat{A} = \{B \mid B \in \mathcal{P}(U), \exists \omega \in B\} \quad (2.13)$$

$$\hat{U} = \{\omega \mid \omega \in U\} \quad (2.13')$$

Given a σ -field \mathcal{B} containing U , $(\mathcal{P}(U), \mathcal{B})$ is a measurable space. A measurable mapping from some factors field $(X_f, \mathcal{B}_f, \mathcal{P}_f)$ to $(\mathcal{P}(U), \mathcal{B})$

$$\xi: X_f \rightarrow \mathcal{P}(U) \quad (2.14)$$

$$\xi^{-1}(B) = \{\omega \mid \xi(\omega) \in B, B \in \mathcal{B}, \forall \omega \in X_f\}$$

is called a random set on U , which is a random variable on $\mathcal{P}(U)$. In what follows, we use $\mathcal{P}(X_f, \mathcal{B}_f; \mathcal{P}(U), \mathcal{B})$ to denote all such random sets.

DEFINITION 2.5 Let $\xi \in \mathcal{P}(X_f, \mathcal{B}_f; \mathcal{P}(U), \mathcal{B})$. Denote

$$\mu_\xi = \{P(\omega \mid \xi(\omega) \in U), \omega \in U\} \quad (2.15)$$

is called the fall-shadow of ξ . Knowledge representation may be used to the fall-shadows.

DEFINITION 2.6 For given random sets $\xi: X_f \rightarrow \mathcal{P}(U)$ and $\eta: X_g \rightarrow \mathcal{P}(U)$

$$\mu_{(\xi, \eta)} = \{P(\omega \mid \xi(\omega) \ni \omega, \eta(\omega) \ni \omega)\} \quad (2.16)$$

is called the union fall-shadow of ξ and η . If $\mu_\xi(\omega) > 0$, denote

$$\mu_{\eta|\xi} = \{P(\eta \ni \omega \mid \xi \ni \omega)\} \quad (2.17)$$

is called the conditional fall-shadow of η when $\xi \ni \omega$.

PROPOSITION 2.1 The necessary condition for independence of ξ

$$\mu_{(\xi, \eta)}(\omega, \omega) = \mu_\xi(\omega) \mu_\eta(\omega) \quad (\forall \omega \in X_f, \omega \in X_g) \quad (2.18)$$

Let μ be a probability measure on the measurable space (U, \mathcal{B}) , and the fall shadow μ_ξ of random set ξ on U is integrable, denote

$$\bar{m}(\xi) = \int \mu_\xi(\omega) m(d\omega) \quad (2.19)$$

We call $\bar{m}(\xi)$ as the mass of self-valued statistics in which each $\xi \in \mathcal{P}(X_f, \mathcal{B}_f; \mathcal{P}(U), \mathcal{B})$ make independent observations $\omega_1, \dots, \omega_n$ self-sample.

$$1, 2, \dots, n \quad \omega_i \in \mathcal{P}(U) \quad (i=1, \dots, n)$$

Denote

$$\bar{m}_n(\xi) = \frac{1}{n} \sum_{i=1}^n \chi_{\omega_i} \quad (2.20)$$

It is called the law of great numbers of fall-shadow ξ on U . In what follows, the fall shadow μ_ξ of ξ is integrable, containing the law of great numbers theorem.

THEOREM 2.1 The law of great numbers of fall-shadow ξ is given

$$\xi_i \in \mathcal{P}(X_f, \mathcal{B}_f; \mathcal{P}(U), \mathcal{B}) \quad (i=1, 2, \dots, n)$$

are independent and have the same distribution $\mu_{\xi_i}(\omega) = \mu(\omega)$. Then

$$\bar{\xi}_n(\omega) = \omega = \frac{1}{n} \sum_{i=1}^n \chi_{\xi_i}(\omega) \quad (2.21)$$

where $\chi_{\xi_i}(\omega) = 1$ if $\omega \in \xi_i$ and 0 otherwise.

$$\bar{\xi}_n(\omega) \xrightarrow{\text{a.e.}} \mu(\omega) \quad (n \rightarrow \infty) \quad (2.22)$$

2.2. Fuzzy Entropy

The fuzzy entropy was first proposed by De Luca and Termini (1972). It is a fuzzy extension of the classical entropy. Let X be a universe of discourse and $\bar{\mathcal{F}}(X)$ be the set of fuzzy subsets of X . A fuzzy entropy is a mapping H from $\bar{\mathcal{F}}(X)$ to $[0, \infty)$ satisfying the conditions:

- (1) $H(A) = 0$ iff A is an ordinary subset of X ;
- (2) $H(A) \leq H(A^*)$ where A^* is any sharpened version of A , i.e., $\mu_{A^*}(x) \leq \mu_A(x) \leq 1/2$ and $\mu_{A^*}(x) \geq \mu_A(x) \geq 1/2$;
- (3) $H(A) = H(\bar{A})$ (\bar{A} is as fuzzy as A).

More recently, De Luca has proposed a general definition of fuzzy entropy:

$$H(A) = - \sum_{x \in X} \mu_A(x) \log \mu_A(x) - \sum_{x \in X} (1 - \mu_A(x)) \log (1 - \mu_A(x)) \quad (2.23)$$

This can be extended to evaluate a whole fuzzy partition $\{A_1, \dots, A_m\}$ and give a measure of the total amount of ambiguity of an object x in deciding to which of A_1, \dots, A_m an element x belongs. If $\{A_1, \dots, A_m\}$ is a fuzzy partition, the fuzzy entropy is

$$H(A_1, \dots, A_m) = - \sum_{x \in X} \sum_{j=1}^m \mu_{A_j}(x) \log \mu_{A_j}(x) \quad (2.24)$$

where $\{A_1, \dots, A_m\}$ is an ordinary partition of X , $\sum_{j=1}^m \mu_{A_j}(x) = 1$. $H(A_1, \dots, A_m)$ is maximum iff $\forall i, \forall j, \mu_{A_j}(x) = 1/m$ (maximal ambiguity).

Let $X_f \subseteq X$ be a factorial space, $\{A_1, \dots, A_m\}$ a fuzzy partition satisfying the condition:

$$\mu_{A_j^*}(x) = \mu_{A_j}(x) \quad \sum_{j=1}^m \mu_{A_j}(x) = 1 \quad (x \in X_f) \quad (2.25)$$

Then the fuzzy entropy of $\{A_1, \dots, A_m\}$ is

$$H(A_1, \dots, A_m) = - \sum_{x \in X_f} \sum_{j=1}^m \mu_{A_j^*}(x) \log \mu_{A_j^*}(x) \quad (2.26)$$

and the fuzzy entropy of $\{A_1, \dots, A_m\}$ is

$$H_f(A_1, \dots, A_m) = \max_{\{A_1, \dots, A_m\} \in \bar{\mathcal{F}}(X_f)} H(A_1, \dots, A_m) \quad (2.27)$$

where $\max_{\{A_1, \dots, A_m\} \in \bar{\mathcal{F}}(X_f)} H(A_1, \dots, A_m)$ is maximum fuzzy entropy, iff $\forall x \in X_f, \mu_{A_j}(x) = 1/m$ and $\{A_1, \dots, A_m\}$ is the fuzzy entropy of $\{A_1, \dots, A_m\}$ in the factorial space $X_f \subseteq X$.

The knowledge of thinking in image may be determined by the clear degree, the fall shadow, the entropy, and information amount of the factors, etc.

2.1.3. THE CONFIDENCE METHOD

The confidence method is a process which computer called "confidence degree based" is a learning process. Usually, the confidence degree is learning learning with teacher's confidence degree and so on. In this section, we will introduce the confidence method.

The confidence method is a kind of psychological measurement method. It is based on the theory of perceived distance. In the confidence method, the experts give out the factors α_i and β_i and the computer give out a group of objects $\{O_1, O_2, \dots, O_m\}$. The degree of object O_i perceived according to the degree of factor to be evaluated must rely upon psychological measurement then we invite some experienced experts to evaluate it according to the basic rule of perceived distance.

For example, we take the following way:

Let us take the headache as an example. In order to detect the degree of headache, a kind of disease, we first draw a line segment whose length is 100 mm. Let's number 1 to 100 mm every 1 mm, and call it "midpoint". Then, participating one with these points as proper positions on the line, in accordance with their own feeling about the degree of headache, denote the first point as F_1 , and F_2 at point from right. The interval $[F_1, F_2]$ of the line is called a person, and $[F_1, F_2]$ is called a confidence interval. Then, according to calculating that according to formula (2.1), we can calculate the confidence degree, and slope, and so on.

Then, we can calculate

$$\alpha = \frac{1}{n} \sum_{i=1}^n \frac{1}{i} \cdot i \quad (2.1)$$

and

$$\beta = \frac{1}{n} \sum_{i=1}^n i \cdot i \quad (2.2)$$

According to (2.1), we may represent the point estimation of confidence degree by use of α . $\bar{\alpha}$ may be called the blindness of the confidence method. The smaller value of $\bar{\alpha}$, the more faithful we are about the estimation, and $\bar{\alpha} = 0$ means quite sure.

When the confidence method is used, we can let each expert puts only one point on the line, but here we let q experts, $1 \leq k \leq q$, to be attached to it. This integer q represents a confidence degree to the point set.

The result obtained from confidence method is $\{\alpha_i, \beta_i, \gamma_i, \delta_i, \epsilon_i\}$.

$$\alpha = \frac{\sum_{i=1}^q \alpha_i}{q}, \quad \beta = \frac{\sum_{i=1}^q \beta_i}{q}$$

is the point estimate of the degree discussed.

The interval estimate and confidence method may be transformed into an algorithm. The more concentrated the points are, the more concentrated the participant is, we can find a functional relationship $\delta = \theta$ between the concentration degree of the points and the confidence degree after putting the points, where θ means the confidence degree and the result of the estimation. For example, finding $f(x_i, \theta_i)$ as a result from the confidence approach, we can transform it into $f(x_i - f(\theta), \theta_i - f(\theta)) \cap [0, 1]$, which can be regarded as a result f in the interval $[x_i - \delta, x_i + \delta]$.

According to the set of problems, μ_{A_j} can be defined as the following: $\mu_{A_j} = \mu_{A_j}(x_i)$, according to (2.9) of (2.9), where the information amount f_i of the objects A_j is $f_i = (f_i \in \Phi), f_i \wedge f_j = 0, i \neq j, i, j \in \{1, 2, \dots, n\}$.

Let $\tau(A_j)$ be the radius of the objects A_j for the fault f_i according to (2.9), where $\tau(A_j) = \tau(A_j)$.

$$\delta_{A_j} = \frac{\sum_{f_i \in \Phi} \tau(A_j) f_i}{\sum_{f_i \in \Phi} f_i} \quad (3.4)$$

where $\tau(A_j)$ is the radius of A_j . The system will give out a wrong conclusion if the system is modified automatically.

For instance, if the image x_0 inputs the computer, then the computer will give out a wrong conclusion A_j , but the correct conclusion is A_k .

$$\mu_{A_j} = \mu_{A_j} \cap \mu_{A_k} \quad (3.5)$$

$$\mu_{A_j} = \mu_{A_k} \cup \mu_{A_j} \quad (3.6)$$

where $\mu_{A_j} = \exp(-\alpha |x_0 - x_j|^2)$, $\mu_{A_k} = \exp(-\alpha |x_0 - x_k|^2)$, α is a constant of the degree according to the expert given.

4. AN EXPERT APPLICATION

In this section, we will provide the thinking in images while the expert is doing the thinking: comparing, analysis, synthesis, and apply, based on experience to modeling human thinking process.

1) Process of Thinking in Images
 The process of thinking in images is a process of using image for comparing, analysis and recognition. For instance, when a doctor diagnoses illness, his thinking process is as follows: he

get a tentative image by examining the total symptoms of the patient's disease, then compare the tentative image with the typical image of kinds of disease according to their experience. The doctor makes a decision by means of analysis and recognition. The following is the mathematical description of comparing, analyzing and recognizing.

Comparing is a kind of divergent thinking. First, the doctor projects the tentative factors space $(f_0, f_0 \in F)$ into the computer projective image $(f_0, f_0 \in F)$ according to tentative examination patient's symptom, then compares the image with typical experience of kinds of disease $(A_j, j=1, \dots, m)$. The process of comparing is actually divided into two steps: First, the computer project sets A_j ; that is, the kinds of disease to tentative factors space $(f_0, f_0 \in F)$, then

calculates the clear degree $\delta_{A_j}(f_0)$ of kinds of disease A_j according to the doctor's experience. Secondly, the doctor thinks of the means of tentative image has more address, so the doctor comparing from integrality aspect, i.e., calculate the clear degree $\delta_{A_j}(f_0)$ of kinds of disease A_j in tentative factors space

$(f_0, f_0 \in F)$. The method is as follows:
 Let $(f_0, f_0 \in F)$ be a tentative factors space, $(f_0, f_0 \in F)$ be the image and sets A_j ($j=1, \dots, m$) be kinds of disease in the factors space of disease $(f_j, f_j \in F)$ ($f_j = \tau(A_j)$), $f_0 < f_j$, then

$$\mu_{A_j}(f_0) = \mu(\downarrow_f A_j) \quad (4.1)$$

where $\downarrow_f A_j$ is the projection from the factors space (f_j) to (f_0) . If $f_0 > f_j$, then

$$\mu_{A_j}(f_0) = \mu(\uparrow_f A_j) \quad (4.2)$$

where $\uparrow_f A_j$ is the cylindric extension from the factors space (f_j) to (f_0) . The clear degree of disease A_j

$$\delta_{A_j}(f_0) = \sum_{f \in f_0} \delta_{A_j}(f) \quad (4.3)$$

is a kind of divergent thinking. First, according to the comparing calculation, we find out a disease or diseases, which is as follows

$$\mu_{A_w}(f_0) = \max_{1 \leq j \leq m} \mu_{A_j}(f_0) \quad (4.4)$$

where $\mu_{A_w}(f_0)$ is the possible $\mu_{A_w}(f_0)$ and the clear degree $\delta_{A_w}(f_0)$ of disease A_w . Therefore, the possible $\mu_{A_w}(f_0)$ and $\delta_{A_w}(f_0)$ are all very large

and factor or result of diagnosis is disease A_w . If the value $\mu_{A_w}(f_0)$ is very large and the $\delta_{A_w}(f_0)$ is

very small, then extend the tentative factors space (f_0) to (f_1) , where $f_0 < f_1$ and $\delta_{A_w}(f_0) < \delta_{A_w}(f_1)$.

Case 2: If the value $|\mu_{Aw}(f_0) - \mu_{Ah}(f_0)|$ is ver. small, then we
can find the tentative factors space (f_0) to (f_t) , where (f_t)

$$|\mu_{Aw}(f_t) - \mu_{Ah}(f_t)| = \max_{i \in S} |\mu_{Aw}(f_t) - \mu_{Ah}(f_t)|$$

Since $\mu_{Aw}(f_0)$ and $\delta_{Aw}(f_0)$ are all ver. small,
we can find the tentative factors space (f_0) to (f_t) , where
 $f_t = \cup_{i \in S} f_i$ and $I(f_t) = \max_{i \in S} I(f_i)$, $f_t \cap f_0 = \emptyset$.

Since $\mu_{Aw}(f_0)$ is ver. small and $\delta_{Aw}(f_0)$ is ver.
big then the knowledge-base should be modified.

The degree of
The degree of synthesis decision making process is
the possible degree and the other degree. We have

$$\mu_{A_j}'(f_0) = \mu_{A_j}(f_0) \cdot \delta_{A_j}(f_0)$$

$$\mu_{Aw}'(f_0) > \lambda \text{ then result of } \mu_{Aw}(f_0) = \mu_{Aw}'(f_0) \cdot w$$

Multiple Consciousness Process

Human thinking is conscious but the thinking process is
complex. In order to model human thinking process, there must be
some simple process in the expert system. The computer
thinking process can be described by a neural network.

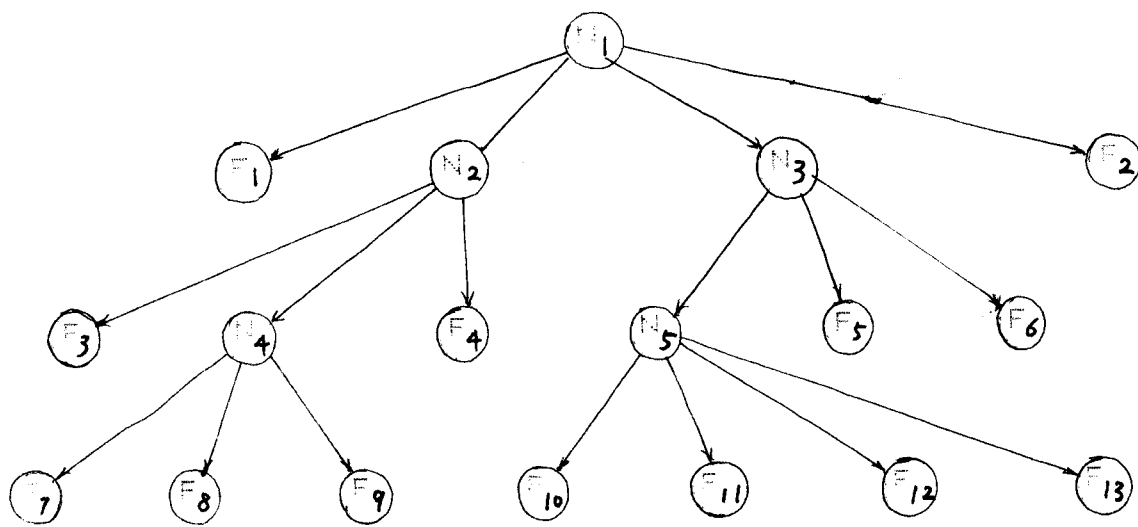
The consciousness tree is a above or below a variable
weight. The nodes on tree is a tree such that each node is a
multiple decision function with variable weights w_j and
input factors f_i , where f_i is the factors of input. Let
 f_i be the factors, we have

$$w_j = \sum_{i=1}^n w_{ij} \cdot f_i \quad (1)$$

where w_{ij} is the varying weight coefficients (see [1] [2]). Human
thinking is a active, the varying weights processing correspond
to human change thinking. Following are experiential rules
1, 2, 3 be finite factors, the varying weight

$$\begin{aligned}
 & 11 \quad 1 \times 2 \times 3 \quad \begin{array}{r} 12 \quad 2 \times 13 \quad 3 \\ \hline 11 \quad 1 \quad 12 \quad 2 \quad 13 \quad 3 \\ \hline 11 \quad 1 \quad 13 \quad 3 \end{array} \\
 & 12 \quad 1 \times 2 \times 3 \quad \begin{array}{r} 11 \quad 1 \quad 12 \quad 2 \quad 13 \quad 3 \\ \hline 11 \quad 1 \quad 12 \quad 2 \end{array} \\
 & 13 \quad 1 \times 2 \times 3 \quad \begin{array}{r} 11 \quad 1 \quad 12 \quad 2 \quad 13 \quad 3 \end{array}
 \end{aligned}$$

where 11, 12, 13 are the path of result w_j for
The result of decision is $w_j = \max_{i \in S} w_j$



N_i is a node and F_j is a leaf
 Fig. 4.1: consciousness-tree

5. CONCLUSION

For the foregoing analysis, we have considered that human thinking process is complex. The complex thinking process contain three kinds of thinking modes, such as logical thinking, thinking in images and inspirational thinking. Every of them may be divided by following three parts:

1. antecedent, 2. contact by intermediary, or consequents
 The main difference one another is disparity in contacting intermediary, logical thinking by rules, thinking in images by experience or imagery and inspirational thinking by human creativity, imagination, conjecture and insight and so on non-logical and super-images function. In this paper, use the method to build a STIM (Shell with Thinking in Images) expert system, which has been applied to the expert systems for diagnosis of fault in aircraft and blood diseases.

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