FUZZY LINGUISTICS ANALYSIS AND ITS APPLICATIONS IN BEHAVIOR INTENTION

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摘　要

傳統應用語言學之研究大都偏向在教學與教育上之探討。但最近一、二十年來，應用語言學研究有著極大的發展，而其研究範圍亦深入各領域，如心理學、社會學、神經認知學等。本研究之目地，乃嘗試應用模糊語言模式來分析並預測人類行爲意願。

我們考慮以模糊語言變數及語言因果關係研究方法，代替傳統之語言等級數值與因果關係方法。主要研究工具爲模糊集合理論與模糊推理。採用模糊分析模式乃爲提昇應用語言學在分析人類行爲意願的眞實性及可靠性。畢竟在數理模式的建構和實際發生的情況裡，模糊分析原理較能處理眞實世界中所面臨的複雜性與不確定性。以目前有關模糊理論發展及模式之改進，未來模糊語言分析系統架構之建立是可預期的。

關鍵字：模糊語言變數、動態語意系統、模糊推理、人類行爲意願，預測

Abstract

Conventional research on applied linguistic is largely concerned with the application in teaching and general education. While in the past twenty years, the field has developed rapidly and has become increasingly interested in various areas, such as psychology, sociology, and neurocongnitive, *etc.*.

In this paper, we present a fuzzy linguistic modeling process to analyze/predict peoples' behavior intention. The approaches we considered are making use of linguistic variables and linguistic causal relationships instead of the numerical variables and relations which are conventional used in systems modeling. The main analytical methods are based on the theory of fuzzy sets and fuzzy logic. The obtained results demonstrate that this kind of fuzzy structure might be dependent on the sort of linguistic rules used, for there seems to exist an intuitive similarity between several linguistic causal relations and the conventional integral, differential or algebraic equations.

Keywords: fuzzy linguistics, dynamic linguistic system, behavior intention, prediction.

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1. Introduction

Conventional research on applied linguistic is largely concerned with the application in teaching and general education. While in the past twenty years, the field has developed rapidly and has become increasingly interested in various areas, such as psychology, sociology, neurocongnitive *etc.*, see Kunnan (1990), Gee (1990), and Jacobs and Schumann (1992). The present research explores one of these fields, sociology, and analyzes/predicts by an alternative approach in applied linguistics, namely on the linguistic modeling for dynamic behavior intention.

In the psychological or sociological study, people are often asked to predict their behavior or intentions. For instance, data on voting intentions have been used to predict American election outcomes since the early 1900s. Hendershot and Placek (1981) reviewed the extensive literature on this field. Surveys of buying intentions have been used to predict consumer purchase behavior since at least the mid-1940s; see Juster (1966).

According to Ajzen and Fishbein (1980) a person's behavioral intention is his subjective probability that the behavior of interest will occur. In practice. social psychologists typically measure intention on some nominal scale and report the statistical correlation between this measure and the behavior outcome. Manski (1990) studied the relationship between stated intentions and subsequent behavior under the *best-case* hypothesis that individuals have rational expectations and that their responses to intentions questions are best predictions of their future behavior. However the use of intentions data to predict behavior has been controversial. Manski (1990) developed a use of intentions data to predict behavior. His result suggests that at least some of the controversy is rooted in the flawed premise that divergences between intentions and behavior sow individuals as a poor predictors of their futures. One of main divergences may reflect the inefficient measure of intention surveys. As recognized by Juster (1966), the yes/no form of intentions questions can be improved upon by asking the respondent to give his probability for the behavior in question.

In the real world, the concepts involved in various domains of information or knowledge are much too complex and sophisticated to admit conventional logic as well as linguistic semantics. Using the fuzzy theory in analyzing the semantic system has contributed not only to attain the rectification of the situation stated above, but also exert a significant impact on the orientation of linguistic semantics. Although there are many different approaches given in the literature, each has its own advantages as well as its own drawbacks.

One of the problems in practical applications of fuzzy theory is how to obtain the membership functions and how to be sure that they do represent the meaning of the linguistic terms. The fuzzy propositional model for the semantic system can account for the degree of typicality and similarity. Which provide a more precise expression in human cognition. It is not difficult to imagine that there exists alternative models that do not directly involve either typicality, similarity and partial similarity membership information. The viability of such models will *mostly* depend on whether it is a satisfactory description of human perceptual primitives.

In this paper, I will present a linguistic modeling process to analyze/predict people's behavior intention. The approaches we considered are making use of linguistic variables and linguistic causal relationships instead of the numerical variables and relations which are usually in systems modeling. The main methods is based on the theory of fuzzy sets. Not much attention will be paid to the basic theory of fuzzy sets, which is assumed the readers are familiar with the theory of formal languages and fuzzy logic. For detailed introduction see Klir and Golger (1988). On the other hand, since Zadeh published a sequence of papers about fuzzy set theory and its applications, fuzzy linguistics has received more and more attention by applied linguists, for examples, see Joyce (1976), Rieger (1976) and Morgan and Pelletier (1977) Sanchez *et al* (1982) *etc.*, Some preliminary results on the fuzzy linguistic system may refer to Lakoff (1973), Rieger (1976), Dubois and Prade (1980), and Zadeh (1985). For an extensive treatment of the theory of fuzzy sets with natural language the interested readers may refer to Dubois and Prade (1980).

2. The fuzzy representation of linguistics

First, we give a brief description about the application of fuzzy set theory to sociological research. In traditional set theory, an element either belongs to a set or it does not. But elements in a fuzzy set may belong only partially to the set. For example, the term *young people*. At what age is someone no longer young? There is no exact critical line, so a fuzzy-set definition might show a person 20 years old as '90 percent young' while some one 60 years old would be only '30 percent young'. The degree of membership in a fuzzy set ranges from 0 to 1. Furthermore, each value of a linguistic variable represents a possibility distribution, see Chang and Sun (1993).

The *linguistic variables* play an important role in the linguistics. The values of a linguistic variable can be generated from a *primary term* (e.g., *good*), a collection of modifiers (e.g., *not, very, slightly* tc.), and the conjunctives (e.g., *and, or*). Such values can be generated by a contex-free grammar. In speaking of the semantic system of a natural language, Langacker (1973) argued that we are referring not only to the fact that the words of the language have meanings but also to the way in which they divide the range of our conceptual experience into categories (p.28). On the other hand, familiar considerations from language and semantic theory cast doubt upon the traditional analysis of propositions as sets of possible worlds. The arguments seem to demonstrate that such an analysis yields a notion of proposition which is insufficiently fine-grained to serve as the object of a belief or a thought.

2.1. Linguistic membership and hedge in fuzzy analysis

A fuzzy linguistic space can be defined by a quintuple $\{A, T(A), U, G, M\}$ in which A is the name of the linguistic variable, $T(A)$ is the term-set of A, that is the set of names of linguistic values that A can assume, where each linguistic value of A, denoted by X, is a fuzzy set over the universe of discourse U. G is a syntactic rule (usually a generative grammar) for generating the names of the values of A, denoted by X, is a fuzzy set over the universe of discourse U. M is a semantic rule for assigning to each X from $T(A)$ its meaning $M(X)$, which is a fuzzy subset over U. A particular name of a linguistic value X is called a term (Zadeh, 1975).

A term-set T which can be generated by this grammar is T(Age) = {*young, old, young or old, young and old, not old, very young, ... not very young and not very old.*}. As in the case of numerial values, the set of possible or admissible values has thus been defined in a structural way and not by simple enumeration.

On the other hand, we want to define the semantics of the linguistic values of the σ-algebra. That is where fuzzy set theory enters the scene, for each linguistic value is defined as a fuzzy set. A fuzzy set is a function which assigns grades of membership of elements to vague concept, for example, the fuzzy set '*young*' might be defined as $\mu_{\text{young}}(20) = 1.0$, $\mu_{\text{young}}(25) = 0.9$, $\mu_{\text{young}}(30) = 0.8$, $\mu_{\text{young}}(40) = 0.5$, and so on. Which denotes that we adhere to the numerical age of 20 a grade of membership of the fuzzy set *young* of 1.0, that means 20 completely belongs to young. The age of 25 belongs with a grade of 0.9 to *young*, and so on.

The essential problem in semantics is to evaluate the meaning of a composite term from knowledge of meaning of each of its atomic subterms. We consider here the meaning of composite terms of the form $h \cdot A$ where h is a linguistic hedge such as *slight of, sort of, very, ...* . The hedge h is viewed as a modifier of the meaning of X. Zadeh (1972) defined some operators that may serve as a basis for modeling hedges. The following definitions are similar to that of Zadeh's except we are now considering in a dynamic fuzzy process.

The adverb (e.g. very, extremely, highly, absolutely, slightly, hard, quite, *etc.*.) is usually called the *linguistic modifier* in the fuzzy set. The linguistic qualifiers we considered here do not form a specific family from the semantic point of view. We place among them numerals including the indenfinite ones (e.g. *little*), some nouns (e.g. *majority*), some pronouns (e.g. *every*), some adverb (e.g. *a lot of, very much*), and others.

Such constructs require the intervention of human tought to provide the logics and Bayesian probability, hence we can hardly assume those complicated phenomenon as *measurable,* not even approximately reasoning. Since that fuzzy methods are rather robust, the exact determination of the membership function is not as important as it might seem at first glance. A satisfactory definition about *fuzzy measure* can be found in Zimmermann (1991, p.45).

One of the basic problems in linguistic is to evaluate the meaning of a composite term from knowledge meaning of its atomic subterms. Here we consider the meaning of composite terms of the form $B = H^{\circ}A$, where A is a primary term and H is a linguistic modifier such as *sort of, very, slightly* etc.. The modifier H is viewed as a modifier of the meaning of A.

Definition 2.1. A linguistic hedge or a modifier is an operation that modifies the meaning of a term or, more generally, of a fuzzy set. If A is a fuzzy set then the modifier m generates the composite term $B = m(A)$.

The following models are frequently used for hedges:

$$\begin{aligned} &\text{normalization: } \mu_{\text{norn}(a)}(A) = \mu_a(A)/(sup\ \mu_a); \\ &\text{concentration: } \mu_{\text{cont}(a)}(A) = \mu_a(A)^c,\ c > 1; \\ &\text{dilation: } \mu_{\text{dil}(a)}(A) = \mu_a(A)^c,\ 0 < c \leq; \end{aligned} \quad (2.1)$$

For instance, $\mu(very\ A) = \mu_a(A)^{1.5}$, $\mu(\text{more or less } A) = \mu_a(A)^{0.5}$ and $\mu(\text{slightly of } A) = \mu(A)^{0.25}$. Thus, a small number of basic functions can produce a wide range of models heldges. As in the case of linguistic variables, the set of possible or admissible values has thus been defined in a structural way and not be simple enumeration.

Example 2.1. Suppose M(A) be the rule that assigns a meaning (i.e. a fuzzy set (primary term)) to the terms $M(A) = \{(t,\mu_{young}(t)) \mid t \in (0,120)\}$ with

$$\mu_{young}(t) = \mu(x) = 1.0I_{20}(x) + .9I_{25}(x) + .8I_{30}(x) + .6I_{40}(x) + .4I_{50}(x) + .2I_{60}(x) + .1I_{70}(x);$$

where $I_t(x)$ is an indicator function; i.e. $I_t(x)=1$ if $x=t$, $I_t(x)=0$ if $x \neq t$

Which denotes that we adhere to the numerical age of 20 a grade of membership of the fuzzy set *young* of 1.0, that means 20 completely belongs to young. The age of 25 belongs with a grade of 0.9 to *young*, and so on. For the term '*very young*' we might take the concentration $c = 2$. Then, the membership function becomes

$$\mu_{very\ young}(t) = 1.0I_{20}(x) + .81I_{25}(x) + .64I_{30}(x) + .36I_{40}(x) + .16I_{50}(x) + .04I_{60}(x) + .01I_{70}(x);$$

On the other hand, the continuous membership function for the term '*young*' might be defined as:

$$\mu_{young}(t) = \begin{cases} 1; & 0 \leq t < 25, \\ \exp\{\frac{-(t-25)}{25}\}; & 25 \leq t. \end{cases}$$

Let us consider the linguistic variable: *Age*. The term set shall be assumed to be

$$T(Age) = \{\text{young, very young, very very young,...}\}$$

The term set can now be generated recursively be using the following rule:

$$T^{i+1} = \{\text{young}\} \cup \{\text{very } T^{i+1}\}$$

That is $T^0 = \phi$, $T^1 = \{\text{young}\}$, $T^2 = \{\text{young, very young}\}$, ... For the semantic rule we only ned to know the meaning of *young* and the meaning of the modifier *very* in order to determine the meaning of an arbitrary term of the term set. If we define '*very*' as the concentration, then the terms of the term set of the structured linguistic variable '*Age*' can be determined, given the membership function of the term '*young*' is known.

Modifiers have two main behaviors, with regard to their effect on the qualifications they modulate. They have either a behavior of reinforcement, such as '*very*' or '*absolutely*', for instance, or a behavior of weakening, such as '*more or less*' or '*slightly*'.

2.2 Operations for possibility measure and fuzzy logic

The need for reasoning in possibilities comes up in everyday experience. When people make a decision based on uncertain information, they intuitively weight the data according their importance and certainty. They then select the course of action which, based on all the evidence, seems most likely to yield a desired result.

Consider for example, the process of decision making. Several intentions may be characteristic of the decision, and the more intentions we consider, the more certain we are that the decision is present. Intentions may not have equal importance — a hamburger meal may owing to money-saving while Chinese food is more specific and more indicative of a particular intention.

For any given n, the intention values in these generalized logic are labeled by real numbers in the unit interval [0,1]. These values can be interpreted as degree of intention. We use intention values and define the primitives by the following equations:

$$\mu_{\bar{A}}(x) = 1 - \mu_A(x),$$

$$\mu_{A \cup B}(x) = \mathrm{Min}(\mu_A(x),\ \mu_B(x)),$$

$$\mu_{A \cup B}(x) = \mathrm{Max}(\mu_A(x),\ \mu_B(x)),$$

$$\mu_A(x) \rightarrow \mu_B(x) = \mathrm{Min}(1,\ 1+\mu_B(x)-\mu_A(x))$$

$$\mu_A(x) \leftrightarrow \mu_B(x) = 1 - |\ \mu_A(x) - \mu_B(x)\ | .$$

Thus, a small number of basic functions can produce a wide range of models hedges. However, such an approach has some limits, which are discussed at length in Lakoff (1973). In the following, we will seek to analyze and explain the dynamic linguistic information by a fuzzy linguistic system and predict people's behavior intention.

3. A Dynamic Linguistic System

The application of these formulations of a fuzzy system are discussed in Negoita (1979). Sugeno (1977) suggested that a system becomes fuzzy when objectivity is associated with subjectivity, and emphasized that it is essential to find out in what sense a system is fuzzy, i.e. is it composed by fuzzy elements or described by a fuzzy dynamics?

It is argued that this numerical character of models constitutes a major disadvantage of the usual simulation method. The disadvantages of such numerical models includes:

(i) the danger of *overstraining* the empirical data to meet the requirement of numerical precision;

(ii) the danger of *overinterpreting* the numerical results of the model;

(iii) the danger of *overstraining* all kinds of actually vague relationships into exact relations, usually by means of simplification, complexity reduction, and approximations.

One possible way to diminish the required amount of precision is to use linguistic variables instead of numerical values. Examples of linguistic values are: *high, low, very low, rather low,* and so on. Similarly one may use linguistics relations between variables instead of numerical relations, such as

John looks like Tom

A become much beautiful than B if B is very high,

and so on. Hence the two constituent parts of any system, its elements and its relationships, have become a linguistic dynamic processes. We will call such kind of conditional statements a dynamic fuzzy linguistic model.

3.1 A Dynamic Linguistic Modeling

We claim that the concept of dynamic linguistic modeling as applied in this research does not refer to the general notation of constructing certain theories, but refers to dynamic linguistic logics. This kind of modeling can as well as be used to empirical situations as in our case.

Let us define a fuzzy dynamic system as $p = \{\mathbf{X}, \mathbf{U}, \mathbf{Y}, \delta, \mathsf{R}\}$; where
$\mathbf{X}$ is the state space,

U is the input space,

Y is the output space,

δ is defined as (**X**, **U**) → **X**, so that at time t, $\mathbf{x}_{t+1} = \delta(\mathbf{x}_t, \mathbf{u}_t)$, is a fuzzy relation which describes the dynamics of the system,

R is defined as **X** → **Y**, a fuzzy relation which gives the output map of the system, i.e. at time t, $\mathbf{y}_t = R(\mathbf{x}_t)$.

As teh title suggests this whole alternative simulation attempt is up to some extent a reaction to the simulation attempted. The main argument against that simulation model, namely the numerical character of it, has already been extensively elaborated. However there are more differences between this model and conventional model.

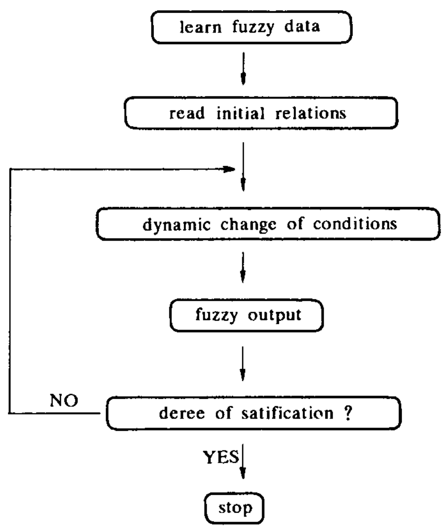

Figure 3.1 A dynamic fuzzy linguistic system

3.2 Fuzzy matrix operation and equations

The dynamic process we used is a fuzzy matrix composition. Fuzzy matrix multiplication is different from classical vector-matrix multiplication. We replace column (row) sums with column (row) maxima. We replace pairwise multiplications with pairwise minima. We denote this **fuzzy matrix composition** relation (Klir and Folger, 1988) by the composition operator '^{o}' for elements of A and B with fuzzy

n-by-n matrix is defined by: $A^oB = R$, where $r_j = \max_{1\leq i\leq n} \min_{1\leq j\leq n} (a_{ij}, b_{ij})$. Note also that the **matrix addition** relation '$\oplus$' for n-by-n matrix is defined by: $A \oplus B = R$, where $r_{ij} = \max_{1\leq i,\, j\leq n} (a_{ij}, b_{ij})$.

Dynamic fuzzy equations are a method to represent people's attitudes or feeling about words/sentences. The semantic differential equation make use of the rating scale which contains pairs of adjectives from positive to negative (bipolar adjectives) meanings. Subjects rate the word on each dimension. The ratings of differet words can be compared.

For instance a rule like '*if* X_t *then* Y_t' represent a linguistic linear equation of the form

$$Y_t = KX_t. \tag{4.1}$$

While the rule like '*if* X_t *then* $Y_t - Y_{t-1}$' might be considered as the linguistic counterpart of the difference equation $Y_t - Y_{t-1} = KX_t$, which is an autoregressive transfer model (*ARX model*). Moreover, the latter equation also corresponds to a differential equation

$$\frac{d}{dt} Y_t = \lim_{\Delta t \to 0} \frac{Y_t - Y_{t-\Delta t}}{\Delta t} = KX_t; \tag{4.2}$$

In the same intuitive way one may argue that a rule of the form '*if* $X_t - X_{t-1}$ *then* Y_t' represents a linguistic integral equation of

$$\int_{t-1}^{t} Y_t \, dt = KX_t; \tag{4.3}$$

Although we should be aware of the fact that there is no rigid mathematical basis for these analogies, this of course does not prevent that there might be a convincing practical basis for them. Previous researches on fuzzy logic applications has indeed established some qualitative comparability including linguistic rules and mathematical equations, see Klir and Folger (1988).

4. Examples

Consider a researcher who wishes to use intentions information to predict/control the behavior of certain response by changing previous behavior intention. So the quantity of interest is: what is the intention B if condition A changes to condition A and the previous information relation is* R. For example, we may be asked by the following question,
Assume that the survey respondents have intentions of their response represented by the linguistic variables {*Very High (VH), High (HI), Medium (ME), Low (LO), Very low (VL)* b and the fuzzy intention values are corresponding to:

$$\textit{intention values} = x_1/VL + x_2/LO + x_3/ME + x_4/HI + x_5/VH \qquad (4.4)$$

For simplicity, we write (4.1) as a vector form (x_1, x_2, x_3, x_4, x_5). We represent the bank of rules as the 5-by-5 linguistic matrix as in Table 4.1

Table 4.1

Linguistic variable	Fuzzy membership				
	VL	LO	MI	HI	VH
VH	.1	.3	.5	.7	.9
HI	.3	.5	.7	.9	.7
ME	.5	.7	.9	.7	.5
LO	.7	.9	.7	.5	.3
VL	.9	.7	.5	.3	.1

Various cases were demonstrated where the change of behavior intention was distinguished by *very low, low, medium, high, and very high.* Dynamic results and predictions are shown below.

Example 4.1.: *How does people's intention change in voting for candidate B if the intention of voting for the party A has changed and the prior relation* R *is: if A then B. (c.f. equation (4.1))*

Situation 4.1.1. If A is low then B is high.

It implies $R = A^oB = (.7,.9,.7,.5,.3)' \circ (.3,.5,.7,.9,.7) = \begin{pmatrix} .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .5 & .5 & .5 \\ .3 & .3 & .3 & .3 & .3 \end{pmatrix}$

If the conditions A changes to VL, then the *intention* B becomes

$$(B \mid A \rightarrow \text{VL}) = AR = (.9,\ .7,\ .5,\ .3,\ .1) \circ \begin{pmatrix} .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .5 & .5 & .5 \\ .3 & .3 & .3 & .3 & .3 \end{pmatrix}$$

$= (.3,\ .5,\ .7,\ .7,\ .7)$, which means B is slightly HI.
If the conditions A changes to ME, then the *intention* B becomes

$$(B \mid A \rightarrow \text{ME}) = AR = (.5,\ .7,\ .9,\ .7,\ .5)' \circ \begin{pmatrix} .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .5 & .5 & .5 \\ .3 & .3 & .3 & .3 & .3 \end{pmatrix}$$

$= (.3,\ .5,\ .7,\ .7,\ .7)$, which means B is slightly HI.
If the conditions A changes to HI, then the *intention* B becomes

$$(B \mid A \rightarrow \text{HI}) = AR = (.3,\ .5,\ .7,\ .9,\ .7) \circ \begin{pmatrix} .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .5 & .5 & .5 \\ .3 & .3 & .3 & .3 & .3 \end{pmatrix}$$

$= (.3,\ .5,\ .7,\ .7,\ .7)$, which means B is slightly HI.

If the conditions A changes to VH, then the *intention* B becomes

$$(B \mid A \rightarrow \text{VH}) = A\mathsf{R} = (.1,\ .3,\ .5,\ .7,\ .9)' \circ \begin{pmatrix} .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .5 & .5 & .5 \\ .3 & .3 & .3 & .3 & .3 \end{pmatrix}$$

$= (.3,\ .5,\ .5,\ .5,\ .5)$, which means B is sort of ME.

Situation 4.1.2. If A is VL then B is VH.

If follows $\mathsf{R} = A^{o}B = (.9,.7,.5,.3,.1)' \circ (.1,.3,.5,.7,.9) = \begin{pmatrix} .1 & .3 & .5 & .7 & .9 \\ .1 & .3 & .5 & .7 & .7 \\ .1 & .3 & .5 & .5 & .5 \\ .1 & .3 & .3 & .3 & .3 \\ .1 & .1 & .1 & .1 & .1 \end{pmatrix}$

If the conditions A changes to LO, then the *intention* B becomes

$$(B \mid A \rightarrow \text{LO}) = A^{o}\mathsf{R} = (.7,\ .9,\ .7,\ .5,\ .3) \circ \begin{pmatrix} .1 & .3 & .5 & .7 & .9 \\ .1 & .3 & .5 & .7 & .7 \\ .1 & .3 & .5 & .5 & .5 \\ .1 & .3 & .3 & .3 & .3 \\ .1 & .1 & .1 & .1 & .1 \end{pmatrix}$$

$= (.1,\ .3,\ .5,\ .7,\ .7)$, which means B is slightly VH.

If the conditions A changes to ME, then the *intention* B becomes

$$(B \mid A \rightarrow \text{ME}) = A^{o}\mathsf{R} = (.5,\ .7,\ .9,\ .7,\ .5) \circ \begin{pmatrix} .1 & .3 & .5 & .7 & .9 \\ .1 & .3 & .5 & .7 & .7 \\ .1 & .3 & .5 & .5 & .5 \\ .1 & .3 & .3 & .3 & .3 \\ .1 & .1 & .1 & .1 & .1 \end{pmatrix}$$

$= (\ 1,\ .3,\ .5,\ .7,\ .7)$, which means B is slightly VH.

If the conditions A changes to HI, then the *intention* B becomes

$$(B \mid A \rightarrow \text{HI}) = A^{o}\text{R} = (.3,\ .5,\ .7,\ .9,\ .7)\ ^{o} \begin{pmatrix} .1 & .3 & .5 & .7 & .9 \\ .1 & .3 & .5 & .7 & .7 \\ .1 & .3 & .5 & .5 & .5 \\ .1 & .3 & .3 & .3 & .3 \\ .1 & .1 & .1 & .1 & .1 \end{pmatrix}$$

= (.1, .3, .5, .5, .5), which means B is sort of positive ME.
If the conditions A changes to VH, then the *intention* B becomes

$$(B \mid A \rightarrow \text{VH}) = A^{o}\text{R} = (.1,\ .3,\ .5,\ .7,\ .9)\ ^{o} \begin{pmatrix} .1 & .3 & .5 & .7 & .9 \\ .1 & .3 & .5 & .7 & .7 \\ .1 & .3 & .5 & .5 & .5 \\ .1 & .3 & .3 & .3 & .3 \\ .1 & .1 & .1 & .1 & .1 \end{pmatrix}$$

= (.1, .3, .5, .5, .5), which means B is sort of HI.

Situation 4.1.3. If A is low then B is low.

$$\text{If follows R} = A^{o}B = (.7,.9,.7,.5,.3)\ ^{o}\ (.7,.9,.7,.5,.3) = \begin{pmatrix} .7 & .7 & .7 & .5 & .3 \\ .7 & .9 & .7 & .5 & .3 \\ .7 & .7 & .7 & .5 & .3 \\ .5 & .5 & .5 & .5 & .3 \\ .3 & .3 & .3 & .3 & .3 \end{pmatrix}$$

If the conditions A changes to VL, then the *intention* B becomes

$$(B \mid A \rightarrow \text{VL}) = A^{o}\text{R} = (.9,\ .7,\ .5,\ .3,\ .1)\ ^{o} \begin{pmatrix} .7 & .7 & .7 & .5 & .3 \\ .7 & .9 & .7 & .5 & .3 \\ .7 & .7 & .7 & .5 & .3 \\ .5 & .5 & .5 & .5 & .3 \\ .3 & .3 & .3 & .3 & .3 \end{pmatrix}$$

= (.7, .7, .7, .5, .3), which means B is sort of LO.

If the conditions A changes to ME, then the *intentions* B becomes

$$(B \mid A \rightarrow \text{ME}) = A^o\text{R} = (.5,\ .7,\ .9,\ .7,\ .5)\ ^o \begin{pmatrix} .7 & .7 & .7 & .5 & .3 \\ .7 & .9 & .7 & .5 & .3 \\ .7 & .7 & .7 & .5 & .3 \\ .5 & .5 & .5 & .5 & .3 \\ .3 & .3 & .3 & .3 & .3 \end{pmatrix}$$

$= (.7,\ .7,\ .7,\ .5,\ .3)$, which means B is sort of LO.

If the conditions A changes to HI, then the *intention* B becomes

$$(B \mid A \rightarrow \text{HI}) = A^o\text{R} = (.3,\ .5,\ .7,\ .9,\ .7)\ ^o \begin{pmatrix} .7 & .7 & .7 & .5 & .3 \\ .7 & .9 & .7 & .5 & .3 \\ .7 & .7 & .7 & .5 & .3 \\ .5 & .5 & .5 & .5 & .3 \\ .3 & .3 & .3 & .3 & .3 \end{pmatrix}$$

$= (.7,\ .7,\ .7,\ .5,\ .3)$, which means B is sort of LO.

If the conditions A changes to VH, then the *intention* B becomes

$$(B \mid A \rightarrow \text{VH}) = A^o\text{R} = (.1,\ .3,\ .5,\ .7,\ .9)\ ^o \begin{pmatrix} .7 & .7 & .7 & .5 & .3 \\ .7 & .9 & .7 & .5 & .3 \\ .7 & .7 & .7 & .5 & .3 \\ .5 & .5 & .5 & .5 & .3 \\ .3 & .3 & .3 & .3 & .3 \end{pmatrix}$$

$= (.1,\ .5,\ .5,\ .5,\ .3)$, which means B is slightly positive ME.

Situation 4.1.4. If A is VL then B is ME.

It follows $\text{R} = A^oB = (.9,.7,.5,.3,.1)'\ ^o\ (.5,.7,.9,.7,.5) = \begin{pmatrix} .5 & .7 & .9 & .7 & .5 \\ .5 & .7 & .7 & .7 & .5 \\ .5 & .5 & .5 & .5 & .5 \\ .3 & .3 & .3 & .3 & .3 \\ .1 & .1 & .1 & .1 & .1 \end{pmatrix}$

If the conditions A changes to LO, then the *intention* B becomes

$$(B \mid A \rightarrow \text{LO}) = A^{o}\text{R} = (.9,\ .7,\ .5,\ .3,\ .1)\ ^{o} \begin{pmatrix} .5 & .7 & .9 & .7 & .5 \\ .5 & .7 & .7 & .7 & .5 \\ .5 & .5 & .5 & .5 & .5 \\ .3 & .3 & .3 & .3 & .3 \\ .1 & .1 & .1 & .1 & .1 \end{pmatrix}$$

$= (.1,\ .5,\ .7,\ .9,\ .5)$, which means B is sort of HI.
If the conditions A changes to ME, then the *intention* B becomes

$$(B \mid A \rightarrow \text{ME}) = A^{o}\text{R} = (.5,\ .7,\ .9,\ .7,\ .5)\ ^{o} \begin{pmatrix} .5 & .7 & .9 & .7 & .5 \\ .5 & .7 & .7 & .7 & .5 \\ .5 & .5 & .5 & .5 & .5 \\ .3 & .3 & .3 & .3 & .3 \\ .1 & .1 & .1 & .1 & .1 \end{pmatrix}$$

$= (.5,\ .7,\ .7,\ .7,\ .5)$, which means B is sort of ME.
If the conditions A changes to HI, then the *intention* B becomes

$$(B \mid A \rightarrow \text{HI}) = A^{o}\text{R} = (.3,\ .5,\ .7,\ .9,\ .7)\ ^{o} \begin{pmatrix} .5 & .7 & .9 & .7 & .5 \\ .5 & .7 & .7 & .7 & .5 \\ .5 & .5 & .5 & .5 & .5 \\ .3 & .3 & .3 & .3 & .3 \\ .1 & .1 & .1 & .1 & .1 \end{pmatrix}$$

$= (.5,\ .5,\ .5,\ .5,\ .5)$, which means B is absolutely no difference.
If the conditions A changes to VH, then the *intention* B becomes

$$(B \mid A \rightarrow \text{VH}) = A^{o}\text{R} = (.1,\ .3,\ .5,\ .7,\ .9)\ ^{o} \begin{pmatrix} .5 & .7 & .9 & .7 & .5 \\ .5 & .7 & .7 & .7 & .5 \\ .5 & .5 & .5 & .5 & .5 \\ .3 & .3 & .3 & .3 & .3 \\ .1 & .1 & .1 & .1 & .1 \end{pmatrix}$$

$= (.5,\ .5,\ .5,\ .5,\ .5)$, which means B is absolutely no difference.

Situation 4.1.5. If A is HI then B is HI.

It follows $R = A^{o}B = (.3,.5,.7,.9,.7)' \circ (.3,.5,.7,.9,.7) = \begin{pmatrix} .3 & .3 & .3 & .3 & .3 \\ .3 & .5 & .5 & .5 & .5 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \\ .3 & .5 & .7 & .7 & .7 \end{pmatrix}$

If the conditions A changes to VL, then the *intention* B becomes

$$(B \mid A \rightarrow \text{VL}) = A^{o}R = (.9,\ .7,\ .5,\ .3,\ .1) \circ \begin{pmatrix} .3 & .3 & .3 & .3 & .3 \\ .3 & .5 & .5 & .5 & .5 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \\ .3 & .5 & .7 & .7 & .7 \end{pmatrix}$$

$= (.3,\ .5,\ .5,\ .5,\ .5)$, which means B is no difference.
If the conditions A changes to LO, then the *intention* B becomes

$$(B \mid A \rightarrow \text{LO}) = A^{o}R = (.7,\ .9,\ .7,\ .5,\ .3) \circ \begin{pmatrix} .3 & .3 & .3 & .3 & .3 \\ .3 & .5 & .5 & .5 & .5 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \\ .3 & .5 & .7 & .7 & .7 \end{pmatrix}$$

$= (.3,\ .5,\ .7,\ .7,\ .7)$, which means B is slightly of HI.
If the conditions A changes to ME, then the *intention* B becomes

$$(B \mid A \rightarrow \text{ME}) = A^{o}R = (.5,\ .7,\ .9,\ .7,\ .5) \circ \begin{pmatrix} .3 & .3 & .3 & .3 & .3 \\ .3 & .5 & .5 & .5 & .5 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \\ .3 & .5 & .7 & .7 & .7 \end{pmatrix}$$

$= (.3,\ .5,\ .7,\ .7,\ .7)$, which means B is slightly HI.

If the conditions A changes to VH, then the *intention* B becomes

$$(B \mid A \rightarrow \text{VH}) = A^{o}\mathsf{R} = (.1,\ .3,\ .5,\ .7,\ .9)\ ^{o} \begin{pmatrix} .3 & .3 & .3 & .3 & .3 \\ .3 & .5 & .5 & .5 & .5 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \\ .3 & .5 & .7 & .7 & .7 \end{pmatrix}$$

$= (.3,\ .5,\ .5,\ .7,\ .7)$, which means B is slightly HI.

The tendency of the model outputs to become more fuzzy with each iteration, has even increased in this case. As a matter of fact the above mentioned intuitive explanation of the fuzzification tendency would imply this result: we have inserted an extra set of vague relations between the vague variables, hence the final vagueness will further increase.

Example 4.2.: *How does people's intention change in voting for candidate B_t if A_t changes and the prior relation* R *is: if A_t then $B_t - B_{t-1}$. (c.f. equation (4.2))*

Suppose the significant changing level $\phi = B_t - B_{t-1}$ and its linguistic values follows Table (4.1).

Situation 4.2.1. If A_t is high, then B_t is higher than B_{t-1} otherwise B_t equals to B_{t-1}.

It follows $\mathsf{R} = A_t\ ^{o}\ \phi_t(\text{HI}) \oplus (not\ A_t)\ ^{o}\ \phi_t(\text{ME})$
$= (.3,.5,.7,.9,.7)\ ^{o}\ (.3,.5,.7,.9,.7)$
$+ (.7,.5,.3,.1,.3)\ ^{o}\ (.5,.7,.9,.7,.5)$

$$= \begin{pmatrix} .3 & .3 & .3 & .3 & .3 \\ .3 & .5 & .5 & .5 & .5 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \\ .3 & .5 & .7 & .7 & .7 \end{pmatrix} \oplus \begin{pmatrix} .5 & .7 & .7 & .7 & .5 \\ .5 & .5 & .5 & .5 & .5 \\ .3 & .3 & .3 & .3 & .3 \\ .1 & .1 & .1 & .1 & .1 \\ .3 & .3 & .3 & .3 & .3 \end{pmatrix} = \begin{pmatrix} .5 & .7 & .7 & .7 & .5 \\ .5 & .5 & .5 & .5 & .5 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \\ .3 & .5 & .7 & .7 & .7 \end{pmatrix}$$

If the condition A_t changes ME, then the intention of change ϕ_t becomes

$$(\phi_t \mid A_t \rightarrow ME) = (.5, .7, .9, .7, .5) \circ \begin{pmatrix} .5 & .7 & .7 & .7 & .5 \\ .5 & .5 & .5 & .5 & .5 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \\ .3 & .5 & .7 & .7 & .7 \end{pmatrix}$$

$= (.5, .5, .7, .7, .7)$, which means ϕ_t is sort of positive medium.

If the condition A_t changes to LO, then the intention of change ϕ_t becomes

$$(\phi_{t+1} \mid A_t \rightarrow LO) = (.7, .9, .7, .5, .3) \circ \begin{pmatrix} .5 & .7 & .7 & .7 & .5 \\ .5 & .5 & .5 & .5 & .5 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \\ .3 & .5 & .7 & .7 & .7 \end{pmatrix}$$

$= (.5, .7, .9, .7, .7)$, which means ϕ_t is slightly positive ME.

Situation 4.2.2. If A_t is very low, then B_t lower than to B_{t-1} otherwise B_t higher than B_{t-1}.

It follows $R = A_t \circ \phi_t(ME) \oplus (not\ A_t) \circ \phi_t(HI)$
$= (.9, .7, .5, .3, .1) \circ (.7, .9, .7, .5, .3)$
$+ (.1, .3, .5, .7, .9) \circ (.3, .5, .7, .9, .7)$

$$= \begin{pmatrix} .7 & .9 & .7 & .5 & .3 \\ .7 & .7 & .7 & .5 & .3 \\ .5 & .5 & .5 & .5 & .3 \\ .3 & .3 & .3 & .3 & .3 \\ .1 & .1 & .1 & .1 & .1 \end{pmatrix} \oplus \begin{pmatrix} .1 & .1 & .1 & .1 & .1 \\ .3 & .3 & .3 & .3 & .3 \\ .3 & .5 & .5 & .5 & .5 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \end{pmatrix} = \begin{pmatrix} .7 & .9 & .7 & .5 & .3 \\ .7 & .7 & .7 & .5 & .3 \\ .5 & .5 & .5 & .5 & .5 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \end{pmatrix}$$

If now A_t changes LO, then the intention of change ϕ_t becomes

$$(\phi_{t+1} \mid A_t \rightarrow LO) = (.7, .9, .7, .5, .3) \circ \begin{pmatrix} .7 & .9 & .7 & .5 & .3 \\ .7 & .7 & .7 & .5 & .3 \\ .5 & .5 & .5 & .5 & .5 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \end{pmatrix}$$

= (.7, .7, .7, .5, .5), which means ϕ_{t+1} is slightly LO.

If now A_t changes to HI, then the intention of change ϕ_t becomes

$$(\phi_{t+1} \mid A_t \rightarrow \text{HI}) = (.3,\ .5,\ .7,\ .9,\ .7) \circ \begin{pmatrix} .7 & .9 & .7 & .5 & .3 \\ .7 & .7 & .7 & .5 & .3 \\ .5 & .5 & .5 & .5 & .5 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \end{pmatrix}$$

= (.5, .5, .7, .7, .7), which means ϕ_t is slightly HI.

Example 4.3: *How does people's intention change in voting for candidate B_t if $A_t - A_{t-1}$ changes and the prior relation* R *is: if A_t is higher than A_{t-1} then B_t. (c.f. equation (4.3))*

Suppose the significant changing level $\phi_t = A_t - A_{t-1}$ and its linguistic values are follows Table (4.1).

Situation 4.3.1. If A_t is higher than A_{t-1} then B_t is high otherwise B_t is low

It follows
$$\begin{aligned} \text{R} &= \phi_t \circ B_t(\text{HI}) \oplus (not\ \phi_t) \circ B_t(\text{LO}) \\ &= (.3,\ .5,\ .7,\ .9,\ .7) \circ (.3,\ .5,\ .7,\ .9,\ .7) \\ &\quad \oplus (.5,\ .7,\ .9,\ .7,\ .5) \circ (.7,\ .9,\ .7,\ .5,\ .3) \end{aligned}$$

$$= \begin{pmatrix} .3 & .3 & .3 & .3 & .3 \\ .3 & .5 & .5 & .5 & .5 \\ .3 & .5 & .7 & .7 & .7 \\ .3 & .5 & .7 & .9 & .7 \\ .3 & .5 & .7 & .7 & .7 \end{pmatrix} \oplus \begin{pmatrix} .5 & .5 & .5 & .5 & .3 \\ .7 & .7 & .7 & .5 & .3 \\ .7 & .9 & .7 & .5 & .3 \\ .7 & .7 & .7 & .5 & .3 \\ .5 & .5 & .5 & .5 & .3 \end{pmatrix} = \begin{pmatrix} .5 & .5 & .5 & .5 & .3 \\ .7 & .7 & .7 & .5 & .5 \\ .7 & .9 & .7 & .7 & .7 \\ .7 & .7 & .7 & .9 & .7 \\ .5 & .5 & .7 & .7 & .7 \end{pmatrix}$$

If now ϕ_t changes to ME, then the intention of B_t becomes

$$(B_t \mid \phi_t \rightarrow \text{ME}) = (.5,\ .7,\ .9,\ .7,\ .5) \circ \begin{pmatrix} .5 & .5 & .5 & .5 & .3 \\ .7 & .7 & .7 & .5 & .5 \\ .7 & .9 & .7 & .7 & .7 \\ .7 & .7 & .7 & .9 & .7 \\ .5 & .5 & .7 & .7 & .7 \end{pmatrix}$$

$= (.7, .7, .7, .7, .7)$, which means B_t is no difference.

If ϕ_t changes to LO, then the intention of B_t becomes

$$(B_t \ \phi_t \rightarrow \text{LO}) = (.7, .9, .7, .5 \ .3) \circ \begin{pmatrix} .5 & .5 & .5 & .5 & .3 \\ .7 & .7 & .7 & .5 & .5 \\ .7 & .9 & .7 & .7 & .7 \\ .7 & .7 & .7 & .9 & .7 \\ .5 & .5 & .7 & .7 & .7 \end{pmatrix}$$

$= (.7, .7, .7, .7, .7)$, which means B_t is sort of no difference.

Situation 4.3.2. If A_t is much lower than A_{t-1} then B_t is low otherwise B_t is very high.

It follows $R = \phi_t \circ B_t(\text{LO}) \oplus (not\ \phi)_t \circ B_t(\text{VH})$
$= (.9, .7, .5, .3, .1) \circ (.7, .9, .7, .5, .3)$
$\oplus (.1, .3, .5, .7, .9) \circ (.1, .3, .5, .7, .9)$

$$= \begin{pmatrix} .7 & .9 & .7 & .5 & .3 \\ .7 & .7 & .7 & .5 & .3 \\ .5 & .5 & .5 & .5 & .3 \\ .3 & .3 & .3 & .3 & .3 \\ .1 & .1 & .1 & .1 & .1 \end{pmatrix} \oplus \begin{pmatrix} .1 & .1 & .1 & .1 & .1 \\ .1 & .3 & .3 & .3 & .3 \\ .1 & .3 & .5 & .5 & .5 \\ .1 & .3 & .5 & .7 & .7 \\ .1 & .3 & .5 & .7 & .9 \end{pmatrix} = \begin{pmatrix} .7 & .9 & .7 & .5 & .3 \\ .7 & .7 & .7 & .5 & .3 \\ .5 & .5 & .5 & .5 & .3 \\ .3 & .3 & .5 & .7 & .7 \\ .1 & .1 & .5 & .7 & .9 \end{pmatrix}$$

If ϕ_t changes to LO, then the intention of B_t becomes

$$(B_t \mid \phi_t \rightarrow \text{LO}) = (.7, .9, .7, .5, .3) \circ \begin{pmatrix} .7 & .9 & .7 & .5 & .3 \\ .7 & .7 & .7 & .5 & .3 \\ .5 & .5 & .5 & .5 & .3 \\ .3 & .3 & .5 & .7 & .7 \\ .1 & .1 & .5 & .7 & .9 \end{pmatrix}$$

$= (.7, .7, .7, .5, .5)$, which means B_t is slightly negative ME.

If now ϕ_t changes to ME, then the intention of B_t becomes

$$(B_t \mid \phi_t \rightarrow \text{ME}) = (.5, .7, .9, .7, .5) \circ \begin{pmatrix} .7 & .9 & .7 & .5 & .3 \\ .7 & .7 & .7 & .5 & .3 \\ .5 & .5 & .5 & .5 & .3 \\ .3 & .3 & .5 & .7 & .7 \\ .1 & .1 & .5 & .7 & .9 \end{pmatrix}$$

$= (.7, .7, .7, .7, .7)$, which means B_t is no difference.

If now ϕ_t changes to VH, then the intention of B_t becomes

$$(B_t \mid \phi_t \rightarrow \text{VH}) = (.1, .3, .5, .7, .9) \circ \begin{pmatrix} .7 & .9 & .7 & .5 & .3 \\ .7 & .7 & .7 & .5 & .3 \\ .5 & .5 & .5 & .5 & .3 \\ .3 & .3 & .5 & .7 & .7 \\ .1 & .1 & .5 & .7 & .9 \end{pmatrix}$$

$= (.5, .5, .5, .7, .9)$, which means B_t is sort of very high.

4.2 Discussions

Although to some extent this might be a reasonable and intuitively logical results, one cannot deny that it is rather annoying: it makes long-term prediction impossible. As a matter of fact one might be more interested to predict that the *intention-decision* will eventually become infinite than to predict that this *intention-decision* decreases during the first few steps. We could state that by avoiding *'the danger of overinterpreting numerical result'* we now ended up at the complementary *'danger of insignificance of linguistic results'*.On the other hand, the most obvious way of reducing fuzziness would be to sharpen the definitions of the spread of the constituent fuzzy sets and fuzzy relations: by diminishing the spread of the fuzzy sets their fuzziness will decrease. However, this would come down to the arbitrariness of the meaning of words, that is, the linguistic values. The second possibility for decreasing the fuzziness in this linguistic system might be to adopt a different set of definitions for fuzzy logic. Though we have chosen a particular definition for fuzzy implication and fuzzy modus ponens (compositional rule of inference), there are other definitions with processing rules might be applied.

5. Conclusion

We have demonstrated that the use of dynamic linguistic variables and relationships in the modeling of human or social processes is to be preferred to the use of numerical models. As Manski (1990) reported there is a great danger in 'overstraining' and 'overinterpreting' the numerical data. The much more vague and unpretentious lingusitic data do not have these disadvantages. Actually it turns out that the lingustic model in every period steadily increases the fuzziness of the results. On the one hand this seems an evident and right phenomenon, on the other hand this blocks the probability of long-term predictions. We have proposed a way to circumvent this problem.

The obtained results seem to differ from those found in Manski (1990) in the sense that the stable state where the behavior intention either tends to zero or to a medium position seems to be of frequent occurrence. It has been suggested that this kind of structural behavior might be dependent on the sort of linguistic rules used, for there seems to exist an intuitive similarity between several linguistic causal relations and the conventionl integral, differential or algebraic equations.

Two general remarks are left to be made. First it should be emphasized that the practical usefulness of the dynamic linguistic system approach can only be proved by actually applying the method. A lot more application studies will have to be performed to study this question. Secondly it would seem to be very useful if one could develop a mathematical tool for the analysis of linguistic model behavior. Up till now only the fuzzy logic controller type of linguistic system has been studied in this sense.

Finally, a neural network is a system of interconnected computational elements operated in parallel, arranged in patterns similar to biological neural nets and modeled after the human brain. Recently interest in this field has increased mainly because of the developments in many fields. Kosko (1992) suggested the use of *neural networks* with application to fuzzy system as a function estimators. We hope this direction of research would provide a useful tool in dynamic linguistic system of behavior intention. However, in order to get an appropriate accuracy for behavior intention, we expect neurocomputing will be a worthwhile approach and will stimulate more future empirical work in semantic analysis as well as applied linguistics models. Therefore, some possible ways about this field will be further researched.

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