Using Cloud Theory to Increase Fuzzy Logic Control System Robustness

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Abstract: The traditional fuzzy control based on the membership function is limited for its mathematic model is accurate once it is defined by the mathematical formula, Cloud theory can deal with uncertainty, including cloud model, virtual cloud, cloud operations, cloud transform, uncertainty reasoning, etc. Cloud model can carry out uncertain transition between a linguistic term of a qualitative concept and its numerical representation. It integrates ambiguity and randomness organically to fit the real world objectively, cannot be replaced in some fields of the human society. The new fuzzy control method based on the cloud theory has good robustness.

Keywords: Fuzzy Logic Control; Cloud Theory; Digital Feature of Cloud Model; Membership Function; Robustness

1. Introduction

Fuzzy logic control is a means of control based on fuzzy set theory; it is a combination product of the fuzzy system theory and fuzzy technology and automatic control technology. In 1965, Professor L.A. Zadeh, U.S. control Expert, founded the fuzzy set theory, it provides a new tool to describe, study and deal with the phenomenon of ambiguity. A new method to design controller based on a system model using fuzzy set theory - fuzzy logic control also will come out [1].

The core of fuzzy logic control is using fuzzy set theory, transform the human control strategy of natural language into the control algorithm described by computer language, this method can not only accomplish the control, but also simulate the human thinking way that can effectively control the objects that we cannot construct a mathematic model to control them. But the membership function was proposed to describe the concept fuzzy degree. Once the fuzzy sets are described by a precise membership function, fuzzy concept are forced into a precise mathematical theory, since then, in all aspects of mathematical thinking and application, the concept is no longer has the slightest ambiguity. This is the defect of traditional fuzzy set theory. A new mathematical theory-cloud theory has the superiority to describe the fuzzy problems [2].

Here, we first look at the mathematical cloud theory.

2. Cloud Theory

Cloud theory can deal with uncertainty, including cloud model, virtual cloud, cloud operations, cloud transform, uncertainty reasoning, etc. Cloud model is a qualitative and quantitative conversion model; it combines ambiguity and randomness organically.

Cloud Model: Set U is a mathematical domain U={x}, T is the language value associated with the U. μT (x) is a stable tendency random number which expressed the elements x subordination of T concept, subordination's distribution in the domain is known as the cloud [3][4].

Cloud mathematical expected curve is its subordination curves from the view of fuzzy set theory. However, "thickness" of the curve is uneven, waist is the most scattered, the top and bottom of the curve are convergent, cloud's "thick" reflects the subordination degree randomness, near to or away from the concept center have smaller subordination randomness, while concept center have the largest subordination randomness, which is consistent with people's subjective feelings, see Fig.1.

Cloud are composed of many cloud droplets, one cloud droplets is a implementation based on the qualitative concept, a single cloud droplets may be insignificant, the details of the cloud maybe different generated in a different time, but the overall shape of the cloud reflects the basic characteristics of the qualitative concepts.

The digital features of the normal cloud characterized by three values with the expectation Ex, entropy En, excess entropy He).

The expected value Ex: the center value of the concept domain, is the most representative qualitative value of the concept, it should be 100% belongs to the concept.

Entropy En: is a qualitative measure of the concept's ambiguity, reflecting the accepted range values of the concept domain.

Hyper entropy He: can be described as entropy En of entropy, reflecting the degree of dispersion of the cloud droplets.

The normal cloud is the most important cloud model, because various branches of the social and natural sciences have proved the normal distribution's universality. The equation of normal cloud showed in Eq. 1,:

$$MEC_A(m) = e^{-\frac{(\mu-Ex)^2}{2En^2}}$$

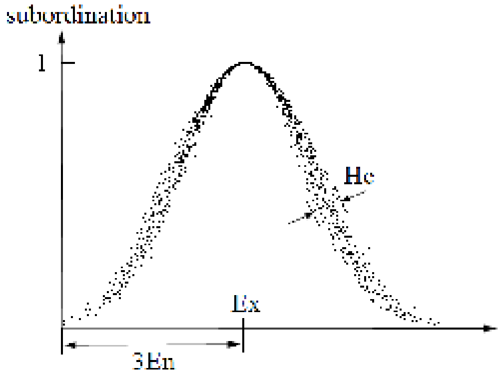

Figure 1. The digital features of the normal cloud

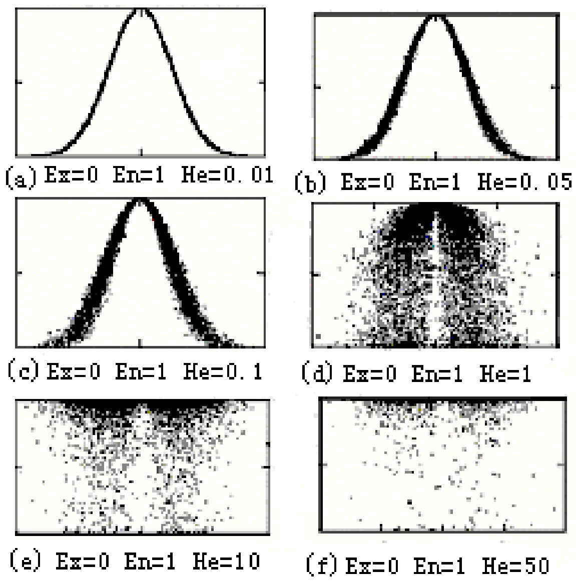

Figure 2. Cloud model changes with He

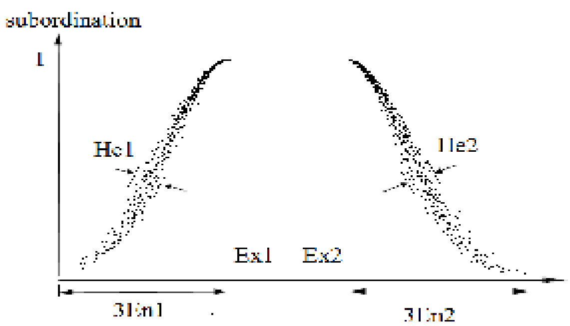

Figure 3. The digital features of Trapezoidal cloud model

Expectation curve is a normal curve, for a qualitative knowledge, the elements outside the Ex±3En in its corresponding cloud model all can be ignored, because it has been proved that approximately 99.74% elements of model fall into the range of Ex±3En by the mathematical characteristics of normal distribution.

We can be seen Fig. 2 (f), although En equal to1, but He is 50, this indicated that the random entropy can be broadly range from -149 to 151 to calculate the degree of membership of each cloud droplets, so that the changes of random entropy will be very large, almost like that each cloud droplet will use a completely different entropy [5].

Thus, use the cloud model to represent the membership function is to determine the digital features of the cloud model, if the concept itself is clear and it is understood consistently by almost all people, you can use smaller En and He. If the concept itself is vague, our understanding is very inconsistent, you can use larger En and He.

Extending the normal cloud model we will get trapezoidal cloud model which is shown in fig.3. Trapezoidal cloud model can be expressed by six values, they are the expected number: Ex1 and Ex2, entropy: En1 and En2, hyper entropy: He1 and He2.

Trapezoidal cloud curve equations are determined by the expectations and the Entropys are following:

$$\begin{aligned}
MEC_A(x) &= e^{-\frac{(x-Ex1)^2}{2En1^2}} \left(Ex1-3En1 <= x <= Ex1\right) \\
MEC_A(x) &= 1 \left(Ex1 <= x <= Ex2\right) \\
MEC_A(x) &= e^{-\frac{(x-Ex2)^2}{2En2^2}} \left(Ex2 <= x <= Ex2+3En2\right)
\end{aligned} \tag{2}$$

Clearly, the left and the right half-cloud expectation curve is a normal curve.

It can complete the qualitative and quantitative transform more accurately, if there is a range belongs to the concept totally, then it can be expressed by the upper edge of Trapezoid, if only one value belongs to the concept totally, then the upper edge of Trapezoid degenerate to a point, trapezoidal cloud model also degenerated into the normal cloud model. He1 and He2 can have different values, and thus the concept of the border on behalf of different fuzzy situation, when the He1 and He2 all degenerate to 0, trapezoidal cloud model expressed a concept with accurate border subordination, when one of the He1 or He2 degenerate to 0, which expressed a concept with one accurate border subordination and one vague border subordination, so trapezoidal cloud model has a better generality. For a trapezoidal cloud, more than 99.74% elements fall into the range of [Ex1-3En1, Ex2+3En2] [6].

Reverse Cloud Algorithm: If a set of data is similar to the normal distribution, we can get the cloud model digital features through reverse cloud algorithm.

In existing similar normal data X, the degree of membership of each element xi Yi value cannot obtain or difficult to obtain; if using the central limit theorem methods to get Yi, then the new error is introduced into the model further. Therefore, a new reverse cloud algorithm was found to improve accuracy of the mapping algorithm. This mapping method is based on the following statistical characteristics of cloud, just use normal data class X value, it is not only simple and easy to promote to high-dimensional data, but also without introduce new error, so accuracy was better than originally reverse cloud algorithms. The new one-dimensional reverse cloud algorithm is as follows:

Algorithm 1: Reverse cloud algorithm

/ * Input: X = (x1, x2 ... xi ..., xn)

Output: The forecasted cloud model expectations Ex, entropy En and hyper entropy He * /

{(1)Calculate the mean of X, Ex = mean (xi) as Ex valuation

(2) Calculate the absolute first-order moment from Ex

$$M1=\frac{1}{n}\sum_{i=1}^{n}|x_i-Ex|$$

(3) calculated second-order square moment from the Ex

$$M2=\frac{1}{n-1}\sum_{i=1}^{n}(x_i-Ex)^2$$

(4) entropy $En=\sqrt{\frac{p}{2}}*M1$

(5) super-entropy $He=\sqrt{M2-En^2}$

}

Proof of the algorithm is as follows: similar normal random variable data X = (x1, x2 ... xi ..., xn), X's mean mean (xi) is the mathematical definition of expected Ex. First-order absolute moment M1 = E|X-Ex|, X probability density function according to probability theory and mathematical statistics is as follows:

$$f(x)=\frac{1}{2pHe}\int_{-\infty}^{+\infty}\frac{1}{y}\exp\{-\frac{(x-Ex)^2}{2y^2}-\frac{(y-En)^2}{2He^2}\}dy$$

The first-order moment:

$$E|X-Ex|=\int_{-\infty}^{+\infty}|X-Ex|f(x)dx$$

put f(x) into the first-order moment:

$$E|X-Ex|=\sqrt{\frac{2}{p}}*\frac{1}{\sqrt{2p}He}\int_{-\infty}^{+\infty}ye^{\frac{(y-En)^2}{2He^2}}dy=\sqrt{\frac{2}{p}}En$$

When there are n data in the similar normal data, then

$$En=\sqrt{\frac{2}{p}}*\frac{1}{n}\sum_{i=1}^{n}|x_i-Ex|=\sqrt{\frac{2}{p}}*M1$$

Second-order square moment

$$M2=\frac{1}{n-1}\sum_{i=1}^{n}(x_i-Ex)^2$$

$$=\int_{-\infty}^{+\infty}(x-Ex)^2dx\int_{-\infty}^{+\infty}\frac{1}{2pHey}\exp\{-\frac{(x-Ex)^2}{2y^2}-\frac{(y-En)2}{2He^2}\}dy$$

$$=\frac{1}{\sqrt{2p}He}\int_{-\infty}^{+\infty}y^2\exp\{-\frac{(y-En)^2}{2He^2}\}dy\int_{-\infty}^{+\infty}\frac{1}{\sqrt{2p}}t^2\exp\{-\frac{t^2}{2}\}dt$$

$$=En^2+He^2$$

Thus we get the digital features of a cloud model which represent language value.

Cloud Transform: Any function can be decomposed into cloud-based superposition with allowed error range, which is Cloud Transform. The equation is:

$$g(x)\approx\sum_{j=1}^{m}c_jf_j(x)\quad(0<g(x)-\sum_{j=1}^{m}c_jf_j(x)<e)$$

g(x): data distribution function

fj(x): cloud-based expectations function

cj :coefficients

m: the number of superimposed cloud,

ε: user-defined maximum error

From the concept of clouds: in the domain the element's subordination to the concept has statistical and random properties. In addition, the high-frequency elements' contributions to the concept are higher than the low-frequency elements. That is the reason to use probability density function of data distribution to get the concept set, so the concept division algorithms can be done.

According to the definition of cloud transform, the quantitative attribute's domain dividing into m concepts can evolve to a problem to get answers from the formula:

$$g(x)=\sum_{j=1}^{m}c_jf_i(Ex1_j,Ex2_j,En1_j,En2_j,He1_j,He2_j)+e_i$$

I.e. to get Ex1j, Ex2j, En1j, En2j, He1j, He2j and cj for each cloud concept, the quantitative attribute domain is divided into a number of concepts by using cloud model, the data in each concept aggregate, and the data between different concepts separated.

Concept division algorithm: Cloud transform recover the data distribution concepts from a large number of property values, the conversion is from quantitative Data to qualitative concept, is a clustering problem essentially. Local peak of the histogram is that the data aggregation part, taking it as a concept center is reasonable, the higher the peak, indicating more data convergence there, deal with it with priority. The concept division algorithm is:

Algorithm 2: Concept division algorithm

Input: the domain of quantitative attributes that need the concept division, the overall error threshold ε, and the peak height error threshold εy, the length error εx between trapezoidal top edge and the minimum value.

Output: m concepts and the corresponding digital features of attribute i.

{

(1) Count the each possible values x of attribute i and get the actual data distribution function g (x);
(2) j=0;
(3) Clouds=; g'(x)=g(x);
(4) while max(g'(x))>ε
(5) { Exj=Find_Ex(g'(x));
(6) Ex1j=search1(g'(x),εy,εx);
(7) Ex2j=search2(g'(x),εy,εx);
(8) En1j=Find_En(cj,Ex1j,ε);
(9) En2j=Find_En(cj,Ex2j,ε);
(10) gj(x)=cj*Cloud(Ex1,En1j,Ex2j,En2j);
(11) g'(x)=g'(x)-gj(x);
(12) j=j+1;
(13) }
(14) for j=0 to m-1 do
(15) {Clouds(Ex1j,=Ex2j,En1j,En2j,He1j,He2j)=
Calculate_He(gj(x), g'(x),Cloud(Ex1j,Ex2j,En1j,En2j));
(16) }
}

In Step 1, use statistical methods to get the actual data distribution function g(x).
Step 2, 3 does variable initialization.
Step 4 the division of the process is ended, if the error limit less than a given error.
Step 5 Search for the peak value of cj of property in the data distribution function g(x), and its corresponding value x is defined as the cloud model center (expectation).
Step 6, 7 search approximate horizon line near the peak (within the error limit threshold εy), if the width is greater than the minimum width of the threshold value εx, where were identified as uniformly distributed, the two endpoints of the line are recorded as the trapezoidal top edge endpoints Ex1j, Ex2j; otherwise get the trapezoidal top edge endpoints are equal to the peak point value Ex1j=Ex2j=Exj, trapezoidal cloud degenerated into the normal cloud. Trapezoidal cloud height coefficient is the function value of the Ex1j or Ex2j.
The step 8, 9 calculate cloud model entropy En1j and En2j to fit g (x) for the half-liter cloud with Ex1j, half-falling cloud with Ex2j. to get En1j searching left area of the cloud model with Ex1j, to get En2j searching right area of the cloud model with Ex2j, the entropy value increase from 0 step from the smaller value until the threshold ε is greater than the difference between the half-normal cloud value and distribution histogram value.
Step10 calculate distribution function of the corresponding Trapezoidal.
Step 11 use the original data minus the known distribution function of trapezoidal cloud model data distribution to get the new data distribution function g'(x).
Repeat step 4 to 12 until the peak value is less than the error threshold.
Step 14, 15, 16 determine half hyper entropy of all cloud model with the residuals of distribution histogram.

3. Using the Cloud Theory to Fuzzy Logic Control

In some traditional control methods, like the washing machine water control can simply be divided into low, medium and high water levels to describe how much water it should have. How much water described by the traditional method are shown in Fig.4. In this method the language value range of water is fixed, that is 29.999L water belong to the low water level will never change, 30.001L water belongs to medium water level will not change forever[8][9][10]. However, the actual difference between these two values is very small, very likely that these two values should correspond to the value of the same language value, but in practical, which language value they should belong to that the washing effect is better? We can do nothing in the traditional fuzzy logic control system, the system can only set at 29.999L water to the low to wash; 30.001L water to medium. It cannot appropriately adjustment wash mode according the washing effect.
The washing water are divided into three cloud models according to the traditional experience, they are shown in Fig. 5.

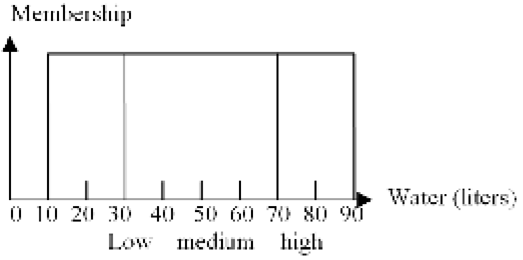

Figure 1. Traditional water amount division method

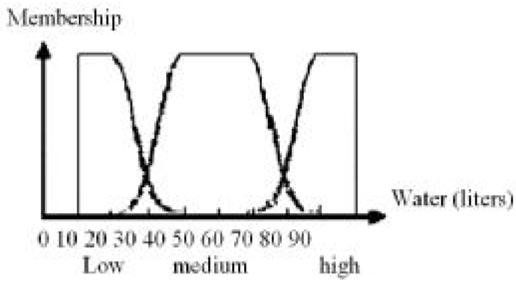

Figure 2. Water amount division method based on cloud model

The digital characteristics of each cloud model can be expressed by six or four digits. When washing, the water level is mapped into the cloud model, can get one of the language values - low, medium and high. From the figure, we can see the value in water between 10 and 20, corresponding to a certain amount of water is low, the water amount is between 40 and 60, corresponding to a certain amount of water is medium, the water amount is between the 80 to 90, corresponding to a certain amount of water is high, But the amount of water between 20 to 40, water amount may be correspond to the low or medium two values, the amount of water is between 60 to 80, it may be corresponded to medium or high two values, which is the characteristics of cloud model. Some of the values belong to which language values have ambiguity and randomness, what is the best, we don't know until we have practiced them, so we let they study themselves。

We use the feature to set a memory component into washing machine, remember these data of every washing :

Actual amount of water

Language value of cloud model

Results of washing effect

Of course, washing effect should be inputted by people, which is key to the system learn intelligently based on the actual situation. Through a period of time, when water falls between 20 and 40, make compares of the real washing effects and the cloud model mapping washing water amount, in the interval, if the washing effect of water amount is low are better, then we can adjust the cloud model digital characteristics, increase the low cloud model expectation value Ex1, while the cloud model expectations which represent medium also be increased. Then the washing machine work according to the new value of the cloud model corresponding washing water, thus altering the amount of water set originally. The system is controlled by the new model, and it relearn again to achieve better water quality.

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