Modeling Method with Probabilistic Fuzzy Logic System for EMG Robot

Yihua Li
School of Traffic and Logistics, Central South University of Forestry and Technology, Changsha 410004, Hunan, China

Wenjing Huang, KeJun Li
*School of Materials Science and Engineering, Central South University of Forestry and Technology, Changsha 410004, Hunan, China
bSchool of Mechanical and Electrical Engineering, Central South University, Changsha 410083, Hunan, China
*Corresponding author (E-mail: m13548573495@163.com)

Abstract
The probabilistic fuzzy logic system is designed for handling the uncertainties with stochastic and nonstochastic features. Electromyographic (EMG) signal is the results of superposition of unit action potential in the process of muscle contracting in people’s hands, there are a lot of uncertainties in the process of EMG signal acquisition and grasp force prediction. In this paper, based on probabilistic fuzzy set by randomly varying the width of Gaussian membership function, the probabilistic fuzzy logic system is designed to model Electromyographic signal in EMG robot. The model results disclose that the probabilistic fuzzy logic system performs better than fuzzy logic system. It is because the probabilistic fuzzy logic system has better modeling ability under uncertain circumstance.

Key words: Probabilistic Fuzzy Set, Probabilistic Fuzzy Logic System, Electromyographic Robot.

1. INTRODUCTION
Type 1 fuzzy set (Zadeh, 1965) is able to model linguistic variable and it can deal with fuzzy information especially the uncertainties related the linguistics. It is noted that the crisp membership grade is used in this set. When the uncertainties are very complex, it may not be suitable to use a crisp membership grade in \([0,1]\), so type-2 fuzzy set (FS) blurs the boundary of type 1 FS to directly model the uncertainty of linguistic expression. Currently, type-1 and type-2 fuzzy set have been successfully applied in many fields such as decision making (Dubois and Prade, 1980), function approximation (Dereli and Baykasoglu, 2011) and so on. Unfortunately, in most of real-world applications, both stochastic and fuzzy uncertainties exist simultaneously, yet the traditional fuzzy theory and probabilistic models are only good at processing one aspect of uncertainties (Yager, 1984). So, it would be valuable to integrate the probability theory with the fuzzy theory. In recent years, several integration strategies have been proposed (L. A. Zadeh, 1995). The probabilistic fuzzy set (PFS) is proposed and developed by introducing the probabilistic theory into the traditional fuzzy set described by center and width. The fuzzy grades in the traditional fuzzy set become the stochastic variables described by the secondary probability density function (PDF). Then the probabilistic fuzzy set that integrates the fuzzy dimension and the probabilistic dimension is able to capture both stochastic and nonstochastic uncertainties. And based on probabilistic fuzzy set, the probability fuzzy logic system is proposed to capture stochastic and nonstochastic uncertainties in engineering process by training the data of the learning sample set. Recently, it has been applied for stochastic modeling and control (Liu and Li, 2005; Li and Wang, 2011), function approximation problem (Zhang and Li, 2012; Zhang and Li, 2012) and so on.

Electromyographic (EMG) signal is results of superposition of unit action potential in the process of muscle contracting in hand. Due to the noninvasive and convenient characteristics of the methods of electricity acquisition electromyographic signal by surface electromyography electrode, most of the prosthetic hands is controlled by surface electromyography in current. Electromyography prosthetic hands can make the Upper limb disabled person independently control the grab mode and the grasp force. In order to realize the electromyographic signal control of the prosthetic hand, the feature is extracted from collected electromyographic signal and then it will establish the relationship between eigenvalues and control command, which enables the disabled man realize operating prosthetic hand by surface electromyography. In order to realize the stability of the prosthetic hand in grasping process, it needs to accurately estimate the grasping force. For example, if fetching an egg, excessive force may make eggs break, and too small force may not be able to grasp stably and it will fall and break. Therefore, an appropriate force is important annulus to achieve stable fetching. At present, there are usually two methods of establishing the relationship between grasp force and surface electromyography, it is as following: the method based on the model and the method based on machine learning. The former method is to establish the relationship of EMG, muscle model and the output force to obtain the grasp force (Ahmet Erdemir and Scott
McLean, 2007); The latter is to establish a nonlinear relationship between EMG signal as input and the force signal as the output, the commonly used method is such as Support Vector Machine (Support Vector Machine, SVM) (Yang and Zhao, 2012; Shahrol Naim Sidek and Ahmad Jazlan Haja Mohideen, 2012) artificial neural network and multivariate nonlinear regression (J. Duque and D. Masset, 1995), etc. In fact, there are a lot of uncertainties in the process of EMG signal acquisition and grasp force prediction, the fuzzy uncertainty produced by man’s subjective consciousness and random uncertainty caused by various noise interference. The probability fuzzy logic system is able to capture uncertainties with both stochastic and nonstochastic nature, so we will apply the probabilistic fuzzy logic system to model EMG signal.

In this paper, the probabilistic fuzzy set is constructed by randomizing the width of Gaussian fuzzy set. Then the related probabilistic fuzzy logic system is designed to model the EMG signal in EMG robot. The results show that the probabilistic fuzzy logic system performs better than fuzzy logic system under random uncertainties. It is because the probabilistic fuzzy set improves the ability of handling complex uncertainties. This work will broaden the application capability of probabilistic fuzzy logic system in engineering.

This paper is organized as following: In section 2, Gaussian probability fuzzy set is constructed; the probabilistic fuzzy logic system is designed in section 3. In section 4, the probabilistic fuzzy logic system is applied to model EMG signal. Finally, the conclusion is given in section 5.

2. THE PROBABILISTIC FUZZY SET BASED ON GAUSSIAN PRIMARY MF WITH RANDOM WIDTH

![Figure 1. Gaussian primary fuzzy MF](image-url)

The Gaussian probabilistic fuzzy set has the primary MF as Gaussian shape described by (1) shown as in Figure 1, the width of Gaussian can be seen as a random variable.

\[
u = e^{-\frac{(x - c)^2}{2\xi^2}}
\]

where \(c\) is the center, and \(\xi\) is the width. The width \(\xi\) in equation (1) can be regarded as a random variable following the normal distribution described as

\[
\xi \sim N(\omega, \lambda^2)
\]

Accordingly, shown as in Figure 2, the probabilistic distribution of fuzzy grade \(U = e^{-\frac{(x - c)^2}{2\xi^2}}\) can be obtained:

\[
F_U(u) = \begin{cases} 
\int_0^{\frac{|x-c|}{2\ln u}} \frac{1}{\sqrt{2\pi} \lambda} e^{-\frac{(\xi-\omega)^2}{2\lambda^2}} d\xi & \text{if } 0 < u < 1 \\
0 & \text{otherwise}
\end{cases}
\]

And the secondary PDF is

\[
Pr ob_{\nu}(u) = \begin{cases} 
\frac{|x-c|}{\sqrt{2\pi} \lambda u} e^{-\frac{(\xi-\omega)^2}{2\lambda^2}} & \text{if } 0 < u < 1 \\
0 & \text{otherwise}
\end{cases}
\]
The probabilistic distribution and the secondary PDF can be derived as follows.

**Proof:**

Suppose the width $\xi$ is a random variable following normal distribution which can be described as:

$$
\xi \sim N(\omega, \lambda^2)
$$

(5)

Then the density function is

$$
\phi(\xi) = \frac{1}{\sqrt{2\pi}\lambda} e^{-\frac{1}{2\lambda^2}(\xi - \omega)^2}
$$

(6)

The random variable fuzzy grade is

$$
U = e^{-\frac{1}{2\xi^2}(x - c)^2}
$$

(7)

$$(u \in (0, 1))$$. Though $U$ is non-monotonic, it is monotonically decreasing in $(0, +\infty)$, so the distribution function of fuzzy grade $U$ can be obtained as following:

Obviously, when $u \leq 0$, the distribution function is

$$
F_U(u) = P(U < u) = 0
$$

(7)

When $0 < u < 1$, the distribution function can be obtained as:

$$
F_U(u) = P(U < u) = P(e^{-\frac{(x-c)^2}{2\xi^2}} < u) = P(P(x-c)^2 > -\frac{2\ln u}{\xi^2})
$$

(8)

As variance $\xi$ must be positive, equation (8) can be written as:

$$
P\left(\frac{(x-c)^2}{-2\ln u} > \xi > 0\right) = \int_0^{\frac{1}{\sqrt{-2\ln u}}} \phi(\xi) d\xi
$$

(9)

Thus, the probabilistic distribution of $U$ is:

$$
F_U(u) = \begin{cases} 
\frac{1}{\sqrt{2\pi}\lambda} e^{-\frac{1}{2\lambda^2}(\xi - \omega)^2} & 0 < u < 1 \\
0 & \text{otherwise}
\end{cases}
$$

(10)

Again, we consider the first derivative of $u$, the probabilistic density function can be obtained from Variable Limit Integral Derivation Formula as:

$$
F_U'(u) = \frac{1}{\sqrt{2\pi}\lambda} e^{-\frac{1}{2\lambda^2}(\xi - \omega)^2} \left(\frac{x-c}{\sqrt{-2\ln u}}\right)'
$$

(11)

$$
= \frac{|x-c|}{\sqrt{2\pi\lambda u}} e^{-\frac{1}{2\lambda^2}(\xi - \omega)^2} (-\frac{1}{2\ln u})
$$

And secondary PDF can be expressed as:

$$
Prob_{\lambda}(u) = \begin{cases} 
\frac{|x-c|}{\sqrt{2\pi\lambda u}} e^{-\frac{1}{2\lambda^2}(\xi - \omega)^2} & 0 < u < 1 \\
0 & \text{otherwise}
\end{cases}
$$

(12)
3. THE DESIGNATION OF PROBABILISTIC FUZZY LOGIC SYSTEM

Compared to the fuzzy logic system, the PFLS based on Gaussian PFS still contain three operations as: fuzzification, inference engine and defuzzification which is shown in Figure 3. In probabilistic fuzzy logic system, probabilistic fuzzy set is the base of the inference, in this section, the Gaussian probabilistic fuzzy set is used in PFLS in the inference process. The inference in PFLS is based on the fuzzy rules (13) as follows:

Rule $j$: If $x_i$ is $A_{i,j}$ and ... and $x_j$ is $A_{j,j}$ and ... and $x_n$ is $A_{n,j}$ Then $y$ is $B_j$

where $A_{i,j} (i=1,2,...,n)$ $(j=1,2,...,J)$ is an antecedent in terms of the $jth$ input variable $x_j$ in the $ith$ rule, and $B_j$ is a consequent part related to the output variable $y$. Here all the antecedent part $A_{i,j}$ and consequent part $B_j$ are Gaussian probabilistic fuzzy set instead of fuzzy set.

The systematic design procedure which is given to design the probabilistic fuzzy logic system for process modeling is as follows:

Step 1) the fuzzy $c$-mean variance (FCMV) algorithm is used to obtain the clustering results as shown in Figure 4. The ellipses denote the clustering, the $c_j$ is the fine clustering center, where $n$ is the number of cluster partition.

Step 2) Cluster centers are projected to $x_1$ and $x_2$ axis to obtain the Gaussian membership function of each clustering. With the clustering result, the secondary PDF can be determined by considering the variation from the mean of Gaussian function.

Step 3) Construct the probabilistic fuzzy logic system.

4. THE MODELING OF EMG SIGNAL BY PROBABILISTIC FUZZY LOGIC SYSTEM

In this section, the PFLS based on Gaussian PFS (GFLS) is applied to EMG robot to model EMG signal under circumstance with random and fuzzy uncertainties.

At present, technologies relating to teleoperator manipulators have developed rapidly. Among them, the approach of applying bioelectrical signals, e.g. electromyography (EMG) signals to control manipulators has become a research hot spot. EMG signals represent the superposition of action potentials of kinematic units in the
contraction of muscles. The control technologies based on EMG signals extract features from the collected EMG signals and build the relationship between eigenvalues and control commands, so that operators can realize remote operation of manipulators. Such a control mode enables manipulators to be moved flexibly and allows human operators to control such robots/manipulators freely and conveniently. These are generally substitutes for humans in operations in dangerous environments and have been applied in industrial and medicine in recent years.

![Figure 5](image)

**Figure 5.** (a): Original EMG signals and EMG signals by using wavelet; (b): Modeling of the manipulator based on EMG signals; (c): Two grasping models: Cylinder grasp and Lateral pinch.

The working principle of manipulators based on EMG control is: The EMG signals obtained from a surface electrode are decoded to acquire a grasping model and the grasping force after data-processing. Then, the signals representing input to the grasping model and the grasping force are transferred to the controller and adjusted. At the same time, the working condition of the manipulator is fed back to the operator to adjust the accuracy of the control. The control of manipulators based on EMG signals includes controls of the grasping model and grasping force as shown in Figure 5 (b). The FLS and GFLS are used to establish models of the relationship between EMG signals and force in two grasping models: lateral pinch and cylinder grasp as shown in Figure 5 (c). The aim is to estimate the magnitude of the applied force and verify the validity of the GFLS.

### 4.1 Data acquisition and pre-processing

As the thumb plays a critical role in grasp, the muscle activities reflecting the state of activity of the thumb are collected. The selected muscles included: the flexor pollicis longus muscle, the palmaris longus, the flexor carpi ulnaris, and the extensor digitorum. In the experiment, the testers wear gloves and move hands to acquire force signals at a sampling frequency of 1,000 Hz in each grasping model. The testers change the magnitude of the applied force in different models, each of which lasted for 15 s. Ten groups of data are obtained across all of the models evaluated.

The EMG signals are subject to interference from various sources of noise. Therefore, wavelet filtering is used to eliminate high-frequency noise in the EMG. Moreover, a notch filter is used to remove power-line interference at 50 Hz during acquisition of the EMG signals. The original signals and de-noised signals are shown in Figure 5 (a). The filtered four-channel EMG signals are adopted as four input signals while force forms the output signal. For the convenience of analysis of the EMG signals in the time domain, a sliding window is used for data-partitioning, with a window length and sliding increment of 256 ms and 64 ms, respectively. At the sampling frequency of 1,000 Hz, the window data and increment are 256 and 64, respectively.

### 4.2 Force prediction model based on EMG signals

A nonlinear modeling is used to approximate the change process of EMG-force about EMG signals.
where $x_i(k), x_j(k), x_k(k)$ and $x_l(k)$ are the input signal and $y(k)$ is the output signal. $f$ is the desired function mapping relationship.

Some pieces of force sensor are pasted in arms, the four input variables are EMG signals of four channels respectively, and the grasping force signal is the output of the system.

4.3 Results and discussion

According to section 3, the modeling process is as follows.

Step 1) The input-output data is 4990, 2500 for training and 2490 for testing.

Step 2) The fuzzy-C mean algorithm clustering is used to obtain the cluster center $c_i (i = 1, 2, ..., l)$, where $l = 5$.

Step 3) Cluster centers are projected to $x_1$ and $x_2$ axis to obtain the fuzzy membership parameters (clustering centers, widths).

Step 4) The triangular membership function of the antecedent part are obtained to construct fuzzy if-then rules. The second PDF which is expressed in equation (4) can be determined by considering the variation from the mean of triangular function. The $l$-th rule in PFLS is:

$$\text{Rule} : \text{If } x_1 \text{ is } A_{1,j}, x_2 \text{ is } A_{2,j}, x_3 \text{ is } A_{3,j} \text{ and } x_4 \text{ is } A_{4,j}, \text{Then } y \text{ is } B_j$$

(15)

Then it is the search of the parameters $\omega$ and $\lambda$ universally, the final modeling results of cylinder grasp mode and lateral pinch mode are shown in Figure 6 and Table 1.

Table 1. (a): The performance compare of force estimation of cylinder grasp mode; (b): The performance compare of force estimation of lateral pinch mode

<table>
<thead>
<tr>
<th></th>
<th>(a) Error(RMSE)</th>
<th>(b) Error(RMSE)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FLS</td>
<td>0.2496</td>
<td>0.3158</td>
</tr>
<tr>
<td>GFLS</td>
<td>0.1735</td>
<td>0.2169</td>
</tr>
</tbody>
</table>

Figure 6. The comparison of modeling results of grasp force between FLS and GFLS. (abscissa axis: time(s); vertical axis: grasp force)
It is shown that the GFLS has a better performance than that of FLS. Because there are a lot of uncertainties in the process of EMG signal acquisition and grasp force prediction, the probability fuzzy logic system is able to capture stochastic and nonstochastic uncertainties, it has better modeling ability under uncertain circumstance.

5. CONCLUSIONS

In this paper, the probabilistic fuzzy logic system is designed to model EMG signal in EMG robot. The results show that the probabilistic fuzzy logic system performs better than fuzzy logic system under random uncertainties. This will broaden the potential application of probabilistic fuzzy logic system.

ACKNOWLEDGEMENTS

This work was supported by 16YBA380(Research project of philosophy and social science in Hunan Province), 16A225(Key project of scientific research in Hunan Education Committee), and was supported by Postdoctoral foundation of Central South University of Forestry and Technology(2015), and was supported by 4336 (Research project of Outstanding Young Scholars in Hunan Education Committee), and also was supported by QJ201511(School Science Fund for Young Scholars)

REFERENCES

L. A. Zadeh. (1965)“Fuzzy sets”, Information and control,10(8), pp.338-353.