EMG Pattern Recognition Based on Artificial Intelligence Techniques

Sang-Hui Park, *Member, IEEE*, and Seok-Pil Lee

***Abstract*— This paper presents an electromyographic (EMG) pattern recognition method to identify motion commands for the control of a prosthetic arm by evidence accumulation based on artificial intelligence with multiple parameters. The integral absolute value, variance, autoregressive (AR) model coefficients, linear cepstrum coefficients, and adaptive cepstrum vector are extracted as feature parameters from several time segments of EMG signals. Pattern recognition is carried out through the evidence accumulation procedure using the distances measured with reference parameters. A fuzzy mapping function is designed to transform the distances for the application of the evidence accumulation method. Results are presented to support the feasibility of the suggested approach for EMG pattern recognition.**

***Index Terms*— Artificial intelligence, electromyographic (EMG), pattern recognition, prosthesis.**

I. Introduction

IT has been proposed that the electromyographic (EMG) signals from the body's intact musculature can be used to identify motion commands for the control of an externally powered prosthesis [1]–[5]. Information extracted from EMG signals, represented in a feature vector, is chosen to minimize the control error [6]. In order to achieve this, a feature set must be chosen which maximally separates the desired output classes. The extraction of accurate features from the EMG signals is the main kernel of classification systems and is essential to the motion command identification [7]. But the nonstationarity of the EMG signal makes it difficult to extract feature parameters precisely with the block processing stationary model such as an autoregressive (AR) model [8]–[10]. And it is very difficult for one feature parameter to reflect the unique feature of the measured EMG signals to a motion command perfectly. Once a feature set has been chosen, a suitable pattern classifier can be used to determine class output.

Several approaches to solve the motion command identification problem using EMG signals have been suggested, e.g., stationary time series modeling (AR model) of the EMG [11]–[13], use of a linear discriminant function [14], use of a learning linear classifier [15], [16], and use of artificial neural networks [6], [17]. Although previous works have resulted in some theoretical and practical achievements for powered prosthetic arms, further advancement such as accurate identification of motion and exact modeling of EMG signals, is required to achieve an ultimate goal [1].

This paper presents an EMG pattern recognition method for more accurate identification of a motion command. The proposed method based on artificial intelligence (AI) [18] is able to accommodate expected interindividual differences and requires little computing time in the pattern recognition with the extracted feature parameters. Based on previous research [1], [6], [15], [19], integral absolute value, difference absolute mean value, variance, autoregressive (AR) model coefficients, and linear cepstrum coefficients, are extracted as feature parameters. Also considering the nonstationary property [9] of EMG signals, the adaptive cepstrum vector [7] is extracted as a feature parameter. To evaluate the utility of the above feature parameters for EMG pattern recognition, a simple separability measure is provided. The Dempster–Shafer theory of evidence [20]–[22] is employed as an evidence accumulation method for the pattern recognition. A fuzzy mapping function is designed for the application of the Dempster–Shafer theory of evidence. Finally, a series of evidence accumulation procedures according to each motion and the recognition error rates are provided.

II. Feature Parameters

The success of any pattern classification system depends almost entirely on the choice of features used to represent the raw signals [6]. It is desirable to use multiple feature parameters for EMG pattern classification since it is very difficult to extract a feature parameter which reflects the unique feature of the measured signals to a motion command perfectly. But the inclusion of an additional feature parameter with a small separability may degrade overall pattern recognition performance [23], [24].

Considering previous works [1], [6], [7], [13], [15], [19], the following feature parameters based on time and spectral statistics are chosen to represent the myoelectric pattern.

1) *Integrated Absolute Value (IAV):* This is an estimate of mean absolute value of the signal, x_i, in segment i which is N samples in length, as given by

$$\overline{x_i} = \frac{1}{N}\sum_{k=1}^{N}|x_k| \tag{1}$$

where x_k is the kth sample in segment i.

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2) *Difference Absolute Mean Value (DAMV):* This is the mean absolute value of the difference between the adjacent samples, k and $k+1$, as defined by

$$\overline{\Delta x_i} = \frac{1}{N-1}\sum_{k=1}^{N-1}|x_{k+1}-x_k|. \quad (2)$$

3) *Variance (VAR):* This is an estimate of the variance of the signal in segment i, as defined by

$$\sigma_i^2 = E\{x_i^2\} - E^2\{x_i\} \quad (3)$$

where $E\{x_i\}$ is the expected value of the signal in segment i.

4) *AR Model Coefficients (ARC):* This is the feature parameter based on spectral statistics and contains information about the location of peaks of the signal on its spectrum.
5) *Linear Cepstrum Coefficients (LCC):* This is the feature parameter based on spectral statistics and comprises the accurate spectrum information of the signals.
6) *Adaptive Cepstrum Vector (ACV):* This is the enhanced feature parameter based on spectral statistics and is extracted by the algorithm which combines with block and adaptive processing.

These features are extracted from each time segment to create the total feature set used to represent the myoelectric pattern. The total number of feature parameters is determined by the number of time segments in the pattern. Although the variance in the time structure of the signals is high, waveform statistics may be stable enough to allow pattern classification. The effect of segment length on classification accuracy must be examined to determine the value which is the best compromise between class information and feature estimation error.

Considering the previous work [6], [11], [13], [25], the segment length and overlap rate was determined to be 64 ms and 0.5, respectively, and the order of filter at ARC, LCC, and ACV was determined to be 6 in this paper. To evaluate the feasibility of the above feature parameters for EMG pattern classification, a simple test of separability measure is provided by the Bhattacharyya distance [26] in the test result. The Bhattacharyya distance $\mu(1/2)$ is used as an important measure of the separability between distributions

$$\mu(1/2) = \frac{1}{8}(\boldsymbol{M}_2 - \boldsymbol{M}_1)^T\left\{\frac{\Sigma_1+\Sigma_2}{2}\right\}^{-1}(\boldsymbol{M}_2 - \boldsymbol{M}_1) + \frac{1}{2}\ln\frac{|(\Sigma_1+\Sigma_2)/2|}{\sqrt{|\Sigma_1||\Sigma_2|}} \quad (4)$$

where $\boldsymbol{M}_1, \boldsymbol{M}_2$ is the mean of class 1 and 2, respectively, Σ_1, Σ_2 is the covariance of class 1 and 2, respectively.

III. Pattern Recognition Based on Evidence Accumulation

There are several factors which must be considered when choosing a classifier or a recognition method for the present application. Due to the nature of the myoelectric signal, it is reasonable to expect a large variation in the value of a particular feature between individuals. Many factors such as changes in electrode position, myoelectric signal training, and body weight fluctuations will produce changes in feature values over time. A suitable recognition method must be able to accommodate the expected individual differences. And it must generate reasonably accurate results with the extracted feature parameters as well as minimize the required computing time for real time prosthesis control [6]. The evidence accumulation method was chosen as the recognition method for this application. Fig. 1 illustrates the schematic diagram of the proposed approach for EMG pattern recognition.

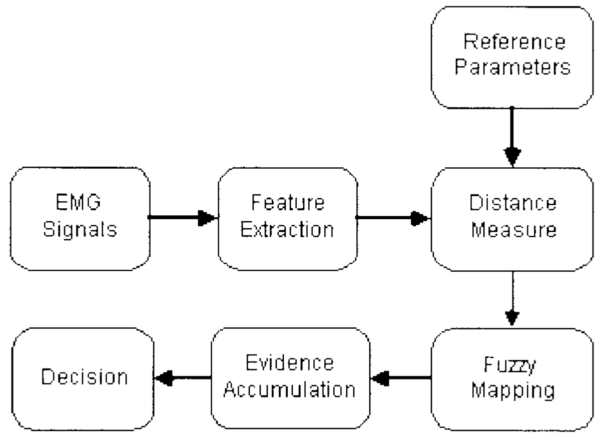

Fig. 1. Schematic diagram.

First of all, the set of feature parameters introduced in Section II is extracted from the sample EMG signals per each movement. The mean of each feature parameter is stored per individual as the reference parameter. And a distance measure between the reference parameters and a set of feature parameters extracted from a test EMG signal is computed. The Euclidean distance [26], [27] is used as the distance measure. Then an evidence accumulation procedure is carried out for pattern recognition where a fuzzy mapping function is used to transform the distances measured for the application of the Dempster–Shafer theory of evidence. Finally the motion corresponding to the EMG signal is identified.

A. Evidence Accumulation

The shortcomings of evidence accumulation schemes commonly employed in rule based expert systems based on the MYCIN model [28] have been recognized. The classical theory and the conventional MYCIN rule have an undesirable flaw in the combining of opposing pieces of evidence—the greater the weights of contradicting evidence, the greater the resulting certainty in their accumulation. In contrast, the Dempster–Shafer theory of evidence not only eliminates that problem but also provides a graceful certainty estimate as such contradictory evidence accumulates [20].

Four components, e.g., evidence for (ef), evidence against (ea), neutral evidence (n), and contradictory evidence (x), are used to represent the evidence of an event in the Dempster–Shafer theory. Each component is a number in the range [0, 1]. The accumulation of evidences for a class is illustrated in Fig. 2.

The combining operator has closure, commutivity, and associativity. Fig. 2(a)–(c), etc., represents feature parameters

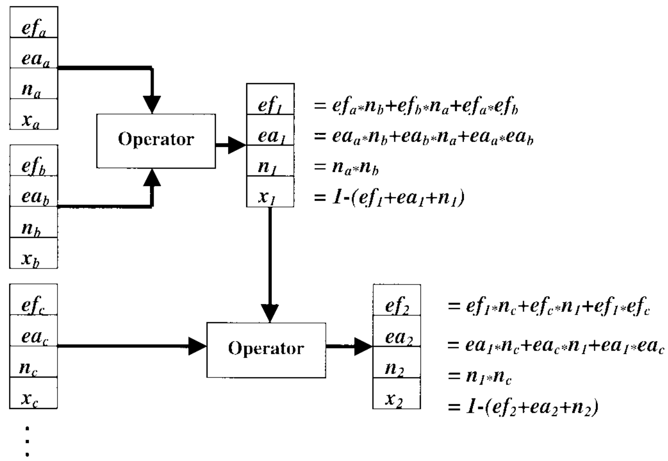

Fig. 2. Evidence accumulation procedure.

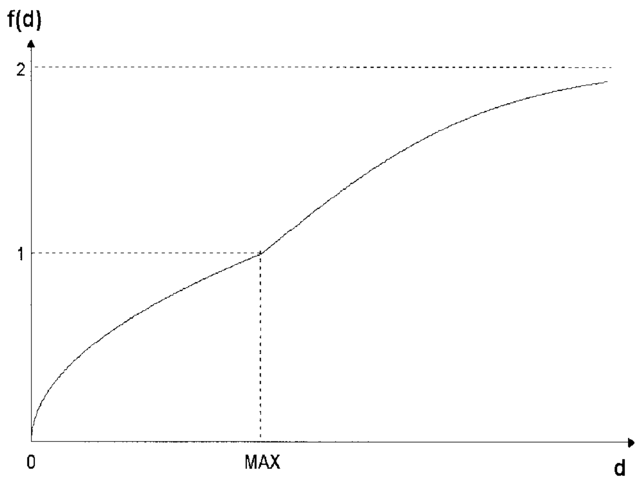

Fig. 3. Fuzzy mapping function.

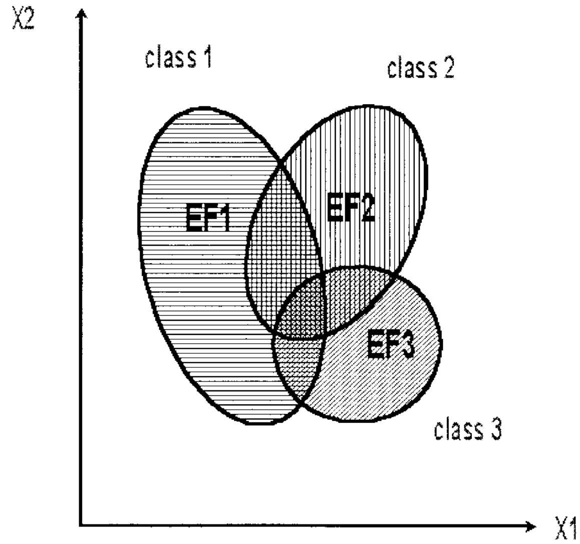

Fig. 4. An example of the evidence boundary.

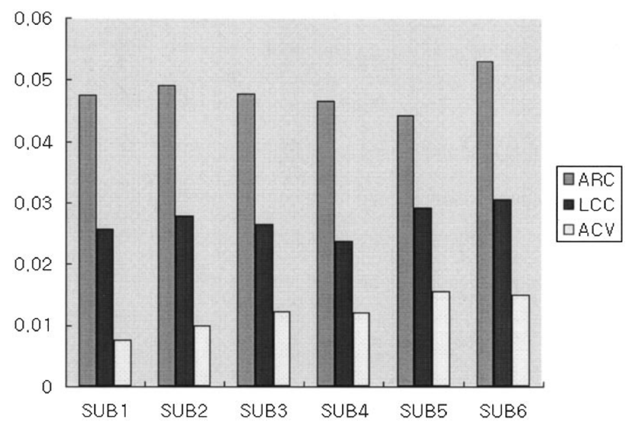

Fig. 5. Mean of variances.

such as IAV, DAMV, VAR, ARC, LCC, and ACV. The evidences for the class computed by using multiple feature parameters, e.g., (a)–(c), etc. in Fig. 2, are accumulated one after another in each class. After the above procedure is done per class, the class which has the maximal final value of ef is chosen as the motion class corresponding to the EMG signal.

B. Fuzzy Mapping

To apply the Dempster–Shafer theory of evidence to EMG pattern recognition, the components of evidence are determined based on the distance d between the sample parameters and a series of feature parameters extracted from the test EMG signals. A fuzzy mapping function $f(d)$ is designed to transform the distance d and is shown in (5) and Fig. 3

$$f(d) = \begin{cases} \sqrt{d/\mathrm{MAX}}, & 0 \le d \le \mathrm{MAX} \\ \dfrac{2}{1+\exp(\mathrm{MAX}-d)}, & d > \mathrm{MAX}. \end{cases} \tag{5}$$

MAX in Fig. 3 is the maximal value of the difference between the mean and the elements in a distribution of each parameter from the sample EMG signals per class per individual. The fuzzy mapping function varies largely at the vicinity of the point where the value of the distance d is MAX. It is useful in pattern recognition since the difference between the values of the functions at the vicinity of the boundary of each class is large [29]. Then the components of evidence are formed as follows:

$$\begin{cases} ef = 1 - f(d), \quad n = 1 - ef & 0 \le d \le \mathrm{MAX} \\ ea = f(d) - 1, \quad n = 1 - ea & d > \mathrm{MAX}. \end{cases} \tag{6}$$

In case the distance d is smaller than MAX, only ef and n exist according to the distance since the input feature parameter can be recognized as the evidence for the class. On the contrary, in the case that d is larger than MAX, only ea and n according to the distance exist since the input feature parameter cannot be recognized as the evidence for the class. The value of each component of evidence according to each feature parameter per motion class can be obtained from (6). Fig. 4 represents an example of the evidence boundary of three classes in two-dimensional (2-D) distribution.

The evidence for each class exists only inside the boundary and the evidence against each class exists only outside the boundary. X1 and X2 represent the feature parameters in Fig. 4. Using the multiple feature parameters defined in Section II, the evidence boundary in a six-dimensional (6-D) distribution is formed.

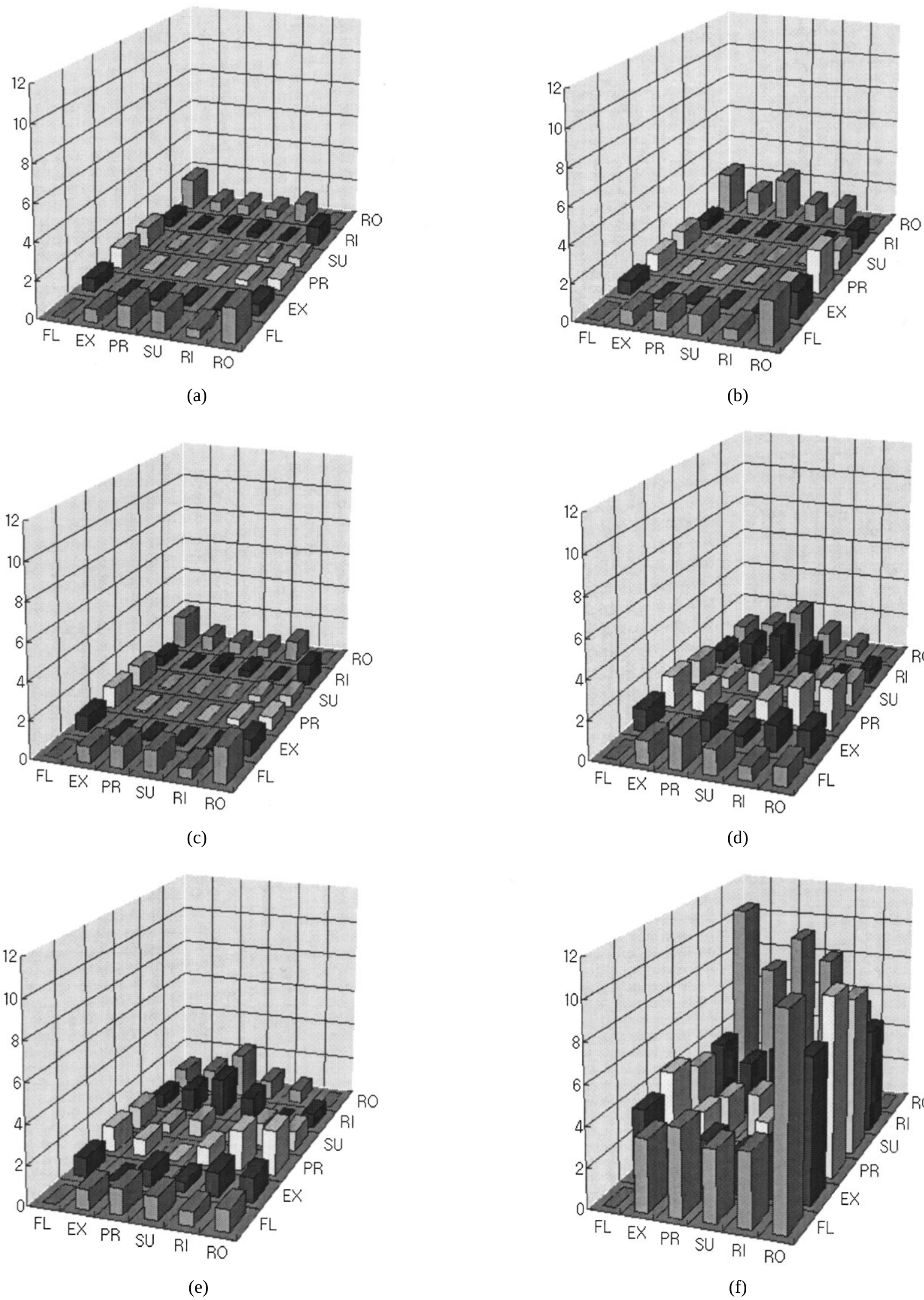

Fig. 6. Separability between classes.

IV. Test Results

Six basic motions, e.g., elbow flexion (FL) and extension (EX), wrist pronation (PR) and supination (SU), and humeral rotation in (RI) and rotation out (RO), were considered as pattern classes.

Floating point surface electrodes, silver/silver chloride pregelled disposable electrodes with hypoallergenic tape, were used to measure the EMG signals. They were located over two sites: on the bulge of biceps brachii and on the lateral head of triceps. The 1 bipolar recording was used to measure the EMG signals. The measured signals were bandpass-filtered (10–500 Hz) and amplified by 1000 and then sampled at 1 kHz. A four-pole Butterworth bandpass filter is used for the test. The EMG signals were recorded for 50 repetitions of each motion from six subjects ages 21–35, with no known

TABLE I
EVIDENCE ACCUMULATION PROCEDURE; FOR TEST SIGNALS BELONGING TO FL

Parameter \ Motion	*FL*	*EX*	*PR*	*SU*	*RI*	*RO*
IAV	(0.594,0, 0.406,0)	(0.203,0, 0.797,0)	(0.373,0, 0.627,0)	(0.594,0, 0.406,0)	(0.642,0, 0.358,0)	(0.053,0, 0.947,0)
DAMV	(0.098,0, 0.902,0)	(0,0.327, 0.673,0)	(0.302,0, 0.698,0)	(0.508,0, 0.492,0)	(0.409,0, 0.591,0)	(0,0.145, 0.855,0)
VAR	(0.103,0, 0.897,0)	(0.399,0, 0.601,0)	(0.472,0, 0.528,0)	(0.696,0, 0.304,0)	(0.702,0, 0.298,0)	(0,0.008, 0.992,0)
ARC	(0.518,0, 0.482,0)	(0.227,0, 0.773,0)	(0.235,0, 0.765,0)	(0.025,0, 0.975,0)	(0.249,0, 0.751,0)	(0,0.171, 0.829,0)
LCC	(0.516,0, 0.484,0)	(0.181,0, 0.819,0)	(0.167,0, 0.833,0)	(0.583,0, 0.417,0)	(0,0.104, 0.896,0)	(0,0.105, 0.895,0)
ACV	(0.651,0, 0.349,0)	(0,0.030, 0.970,0)	(0.103,0, 0.897,0)	(0,0.250, 0.750,0)	(0,0.114, 0.886,0)	(0,0.295, 0.705,0)
Accumulated Evidence	(0.973,0, 0.027,0)	(0.454, 0.106, 0.198,0.242)	(0.868,0, 0.132,0)	(0.732,0.006, 0.018,0.244)	(0.756,0.009, 0.038,0.197)	(0.024,0.526, 0.420,0.030)

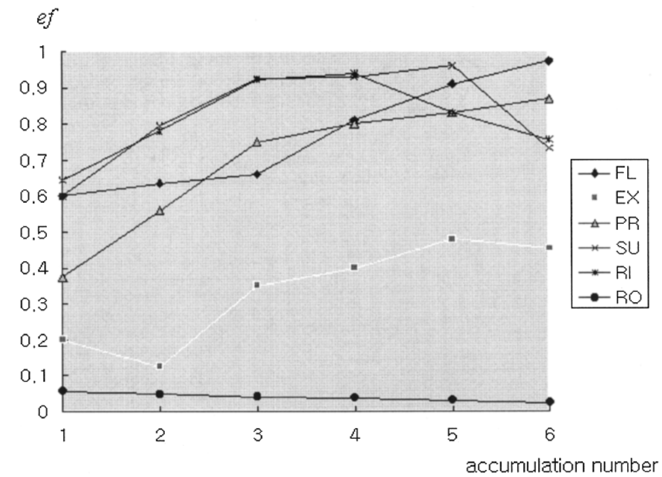

Fig. 7. Value of ef according to the procedure of evidence accumulation for test signals belonging to FL.

neurological or neuromuscular deficits. The recording time is 1 s for one time.

Fig. 5 shows the mean values of variances of ARC, LCC, and ACV per subject.

As shown in Fig. 5, ACV presented a stable feature for EMG signals since the variances of ACV are smaller than those of ARC and LCC. Fig. 6 presents the separability between classes for the tested parameters: IAV, DAMV, VAR, ARC, LCC, and ACV, by the Bhattacharyya distance. As shown in Fig. 6, ACV is superior to the other feature parameters in separability for EMG pattern classification.

An example of evidence accumulation procedure according to the test EMG signals is shown in Table I. The evidence is represented as (ef, ea, n, x) in Table I. The variation of the value of ef according to the procedure of evidence accumulation is represented in Fig. 7. The number on the x-axis represents the accumulation number in Fig. 7. The maximal value of the number is six since there are six feature parameters.

As shown in the evidence accumulation procedure, the proposed classifier recognized the desired motion corresponding to the test EMG signals as the motion with the maximal final value of ef, although there are some undesirable evidences resulted from the inaccurate feature parameters. The recognition error rates with several methods per motion are shown in Table II. The error rates in Table II are normalized by those used for ARC since the recognition error rates depend on the experimental environment.

TABLE II
RECOGNITION ERROR RATES: USING THE DISTANCES WITH ARC (A); WITH LCC (B); WITH ACV (C); USING THE SUM OF THE DISTANCES WITH MULTIPLE PARAMETERS (D); USING THE EVIDENCE ACCUMULATION METHOD WITH MULTIPLE PARAMETERS (E)

Motion \ Method	A	B	C	D	E
FL	1.000	0.879	0.727	0.667	0.455
EX	1.000	1.032	0.806	0.484	0.194
PR	1.000	0.909	0.682	0.727	0.364
SU	1.000	0.750	0.556	0.414	0.278
RI	1.000	0.903	0.774	0.806	0.645
RO	1.000	0.678	0.424	0.254	0.169

V. CONCLUSIONS

We proposed an EMG pattern recognition method to identify motion commands for the control of a prosthetic arm by evidence accumulation with multiple parameters. A series of evidence accumulation procedure showed that the proposed method recognized the desired motion efficiently with the multiple incomplete feature parameters. And the separability test showed that ACV is more feasible for EMG pattern classification than the other feature parameters. Also, the recognition error rates showed that the proposed recognition method is superior to the other methods for EMG pattern recognition. This approach to EMG pattern recognition focuses on generating reasonably accurate results with less computing time using the extracted feature parameters and little subject training, it seems advantageous over other techniques that require considerable training. Further work is recommended to find the optimal feature parameters to be used as inputs to the EMG pattern classifier and to enhance the decision algorithm for more precise pattern recognition with the accumulated evidences.

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