EMG Pattern Recognition based on Evidence Accumulation for Prosthesis Control

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Abstract

We present a method of electromyographic(EMG) pattern recognition to identify motion commands for the control of a prosthetic arm by evidence accumulation with multiple parameters. 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 the 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.

I. Introduction

It has been proposed that the electromyographic(EMG) signals from the bodys intact musculature can be used to identify motion commands for the control of an externally powered prosthesis [1-5]. The information extracted from the 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 seperates the desired output classes. The extraction of precise features from the EMG signals is the main kernel of classification systems and is essential to the motion command identification[7]. But the nonstationarity involved in the EMG signals makes it difficult to extract a feature parameter which reflects the unique features of the measured signals to a motion command perfectly as well as difficult to extract feature parameters precisely with the block processing stationary model such as an autoregressive(AR) model[8-10]. Once a feature set has been chosen, a suitable pattern classifier can be used to determine class output.

For the purpose of solving the motion command identification problem using EMG signals, several approaches such as modeling the EMG signals as a stationary time series(AR model)[11-13], using linear discriminant function[14], learning linear classifier[15, 16], and neural network[6, 17], have been suggested. Although previous works have brought some sort of theoretical and practical achievements for a prosthetic arm, further advancement such as accurate identification of motion and exact modeling of EMG signals, is required to achieve an ultimate goal[1].

We present an EMG pattern recognition method for preciser identification of a motion command. The proposed method based on artificial intelligence(AI)[18] is able to accommodate the expected individual difference with little subject training as well as has less computing time in the pattern recognition with the extracted feature parameters. At first, based on the previous researches[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. And considering nonstationary property[9] of EMG signals, adaptive cepstrum vector[7] is extracted as a feature parameter. To evaluate the feasibility of the above feature parameters for EMG pattern recognition, a simple separability measure is provided. Then a 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 procedure according to the 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

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feature parameter which reflects the unique feature of the measured signals to a motion command perfectly. But the using of the additional feature parameter having a small separability may debase the overall efficiency for a pattern recognition[23, 24].

Considering the previous works[1, 6, 7, 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 the feature parameter based on time statistics and is an estimate of mean absolute value of the signal, $\overline{X_i}$, 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.

2) Difference Absolute Mean Value(DAMV) — This is the feature parameter based on time statistics and is the mean absolute value of the difference between the adjacent samples, k and k+1, as defined by

$$\overline{\triangle X_i}=\frac{1}{N-1}\sum_{k=1}^{N-1}|X_{k+1}-X_k| \tag{2}$$

3) Variance(VAR) — This is the feature parameter based on time statistics and is an estimate of the variation of the signal $\overline{X_i}$ in segment i, as defined by

$$\sigma_i^2=E\{X_i^2\}-E^2\{X_i\} \tag{3}$$

where $E\{X_i\}$ is the expectation value of $\overline{X_i}$.

4) AR model coefficients(ARC) — This is the feature parameter based on spectral statistics has the peak information 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[7] 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 a value which is the best compromise between class information and feature estimation error[6].

Considering the previous works[11, 13, 25], the segment length and overlap rate are determined as 64ms and 0.5, respectively and the order of filter at ARC, LCC, and ACV is determined as 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 results. The Bhattacharyya distance $\mu(1/2)$ is used as an important measure of the separability between distributions.

$$\mu(1/2) = \frac{1}{8}(M_2-M_1)^T\left\{\frac{\Sigma_1+\Sigma_2}{2}\right\}^{-1}(M_2-M_1) + \frac{1}{2}\ln\frac{|(\Sigma_1+\Sigma_2)/2|}{\sqrt{|\Sigma_1||\Sigma_2|}} \tag{4}$$

where $\mathbf{M}_1$, $\mathbf{M}_2$ 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 has less computing time for real time prosthesis control[6]. The evidence accumulation method is chosen as the recognition method for this application. Fig. 1 illustrates the schematic diagram of the proposed approach for EMG pattern recognition.

First of all, a series of feature parameters introduced in section II is extracted per motion from the sample EMG signals. The mean of each feature parameter is stored per individual as the reference parameter. And a distance measure between the reference parameters and a series of feature parameters extracted from the test EMG signals is executed. The Euclidean distance[26, 27] is used for that measure. Then an evidence accumulation procedure is carried out for pattern recognition with the distances transformed by a fuzzy mapping function which is designed to transform the distances measured for the application of the Dempster-Shafer theory of evidence employed in this paper. Finally the motion corresponding to the EMG signals is identified.

1. Evidence Accumulation

The shortcomings of evidence accumulation schemes commonly employed in rule based expert systems based on the MYCIN model have been recognized[28]. The classical theory and the conventional MYCIN combing rule have a very undesirable flaw in the combining of opposing pieces of evidence — the greater the

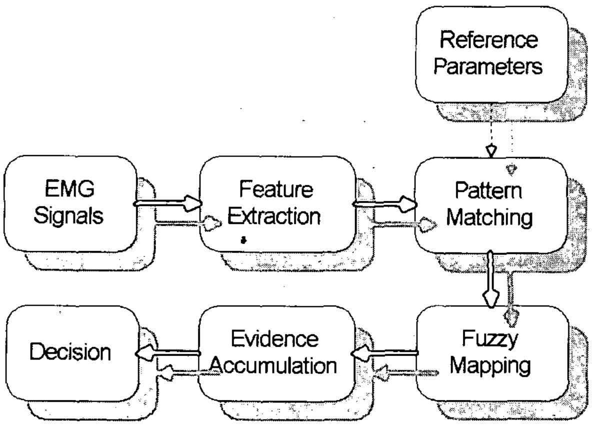

Fig. 1. Schematic diagram.

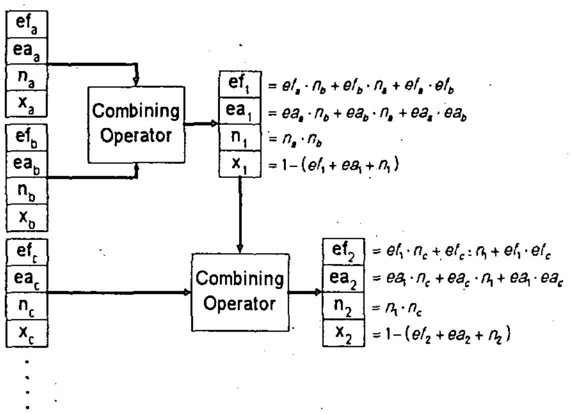

Fig. 2. Evidence accumulation procedure.

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 gracefully degrading 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 an evidence in the Dempster-Shafer theory. Each component is a number in the range[0, 1]. The accumulation of evidences is illustrated in Fig. 2.

The combining operator has closure, commutivity, and associativity. In each class, the evidences for the class computed by using multiple feature parameters, e.g., a, b, c, etc. in Fig. 2, are accumulated one after another. After the above procedure is done per class, the class which has the maximal final value of ef is chosen as the motion corresponding to the EMG signals.

2. *Fuzzy Mapping*

To apply the Dempster-Shafer theory of evidence in the EMG pattern recognition, the components of evidence are determined

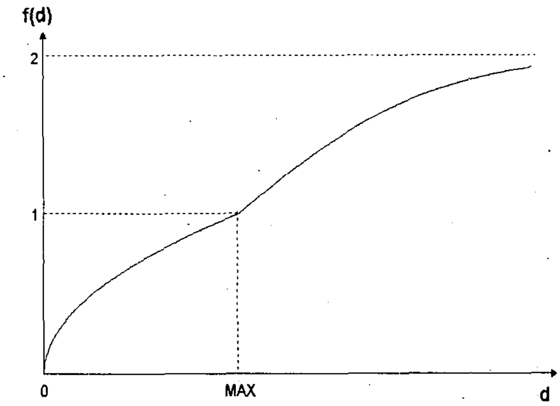

Fig. 3. Fuzzy mapping function.

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.

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

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 that the value of the distance d is MAX. It is for being of help to pattern recognition by means of making the difference between the values of the functions large at the vicinity of the boundary of each class[29]. Then the components of evidence are formed as follows:

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

In case the distance d is smaller than MAX, only ef and n according to the distance exist since the input feature parameter can be recognized as the evidence for the class. On the contrary, in case the distance 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 3 classes in two dimensional distribution.

The evidence for each class exists only in inside of the boundary and the evidence against each class exists only in outside of the boundary. $X1$ and $X2$ represent the feature parameters in Fig. 4. Using the multiple feature parameters referred in section II, the evidence boundary in six dimensional distribution is formed.

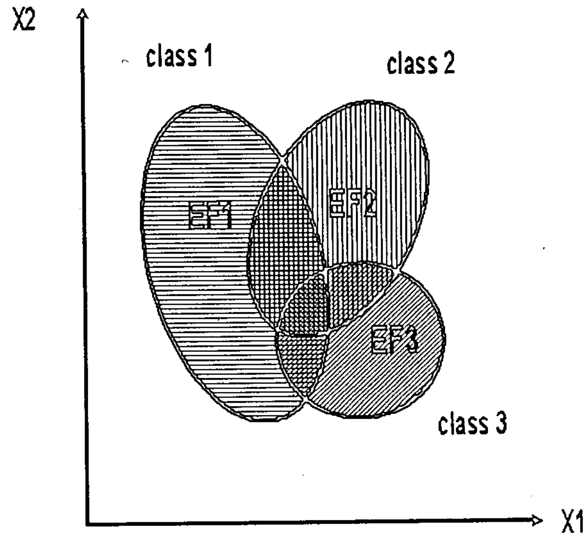

Fig. 4. An example of the evidence boundary.

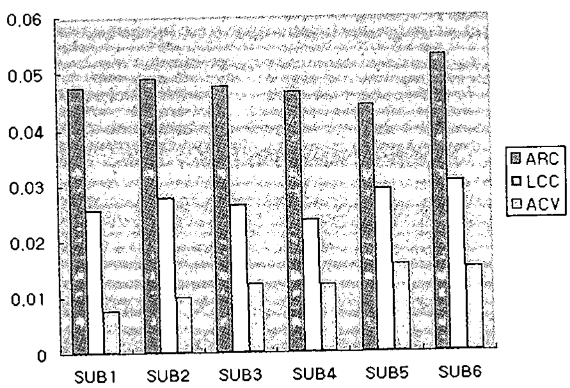

Fig. 5. Mean of variances.

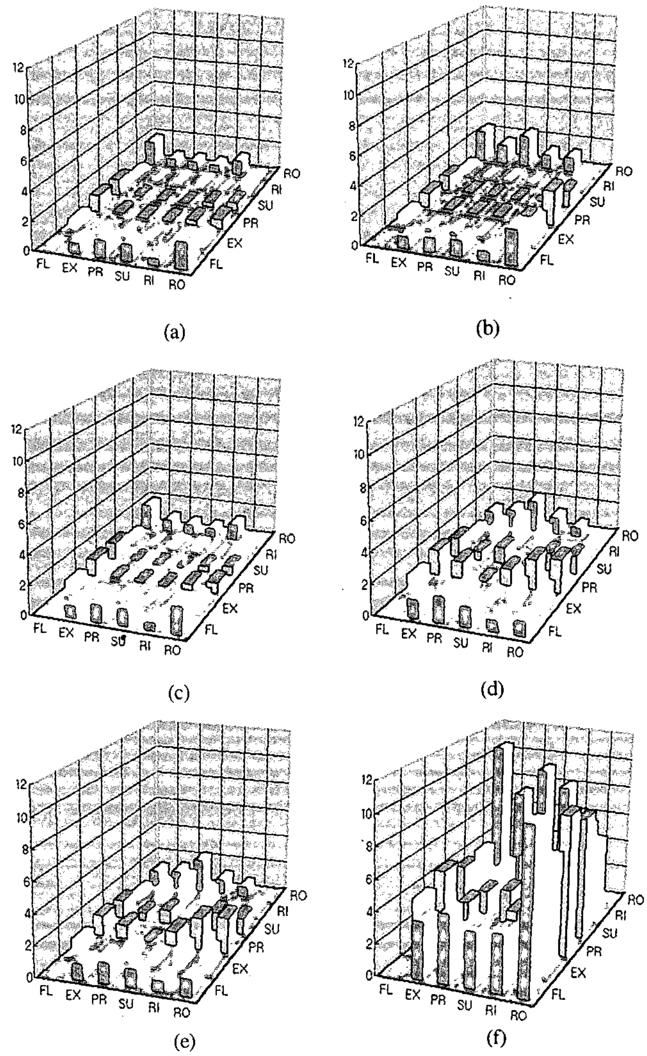

Fig. 6. Separability between classes.

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*), are considered as pattern classes.

Floating point surface electrodes, silver/silver chloride pregelled disposable electrodes with hypoallergenic tape, are used to measure the EMG signals. They are located in two sites: one is just on the bulge of biceps brachii and the other is in the lateral head of triceps. The measured signals were bandpass-filtered (10-500 Hz) and 1000 times amplified and then sampled at 1kHz. The EMG signals were obtained from six subjects through 50 times per each motion.

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

As shown in Fig. 5, ACV presented stable property for EMG signals since the variances of ACV are smaller than those of ARC and LCC. Fig. 6 represents the value of the separability between classes with the multiple parameters, e.g., 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 the separability for EMG pattern classification.

A series of evidence accumulation procedure according to the test EMG signals is shown in Table 1, Table 2, Table 3, Table 4, Table 5, and Table 6, respectively. The evidence is represented as (*ef, ea, n, x*). The variation of the value of *ef* according to the procedure of evidence accumulation is represented in Fig. 7, Fig. 8, Fig. 9, Fig. 10, Fig. 11, and Fig. 12, respectively.

As shown in above evidence accumulation procedure, the proposed classifier recognized the desired motion corresponding to the test EMG signals based on the other evidences by means of choosing the motion which has the maximal final value of *ef*, though some of evidences by the inaccurate feature parameters provided the cause of recognition error. The recognition error rates with several methods per motion are shown in Table 7. The error rates of Table 7 are normalized by those using the distance

Table 1. Evidence accumulation procedure; for test signals belonging to *FL* from subject 1.

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, 0.42,0.03)

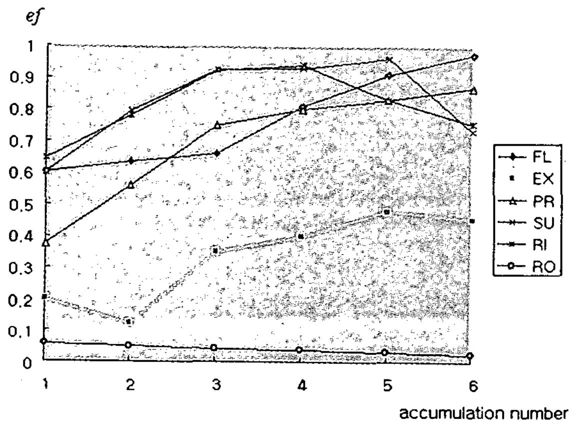

Fig. 7. Value of *ef* according to the procedure of evidence accumulation ; for test signals belonging to *FL* from subject 1.

Table 2. Evidence accumulation procedure; for test signals belonging to *EX* from subject 2.

Parameter \ Motion	*FL*	*EX*	*PR*	*SU*	*RI*	*RO*
IAV	(0.156,0, 0.844,0)	(0,0, 1.000,0)	(0,0.219, 0.781,0)	(0,0.516, 0.484,0)	(0.430,0, 0.570,0)	(0.489,0, 0.511,0)
DAMV	(0.458,0, 0.542,0)	(0.096,0, 0.904,0)	(0.384,0, 0.616,0)	(0.036,0, 0.964,0)	(0.579,0, 0.421,0)	(0.402,0, 0.598,0)
VAR	(0,0.119, 0.881,0)	(0.733,0, 0.267,0)	(0,0.335, 0.665,0)	(0.215,0, 0.785,0)	(0.538,0, 0.462,0)	(0.468,0, 0.532,0)
ARC	(0.522,0, 0.478,0)	(0.306,0, 0.694,0)	(0.264,0, 0.737,0)	(0,0.317, 0.683,0)	(0.214,0, 0.786,0)	(0.011,0, 0.989,0)
LCC	(0,0.047, 0.953,0)	(0.405,0, 0.595,0)	(0,0.272, 0.728,0)	(0,0.128, 0.872,0)	(0.110,0, 0.890,0)	(0.117,0, 0.883,0)
ACV	(0,0.387, 0.613,0)	(0.672,0, 0.328,0)	(0,0.990, 0.010,0)	(0,0.387, 0.613,0)	(0.041,0, 0.959,0)	(0,0.226, 0.774,0)
Accumulated Evidence	(0.402,0.106, 0.113,0.379)	(0.967,0, 0.033,0)	(0.002,0.452, 0.002,0.544)	(0.043,0.623, 0.134,0.200)	(0.926,0, 0.074,0)	(0.664,0.032, 0.110,0.194)

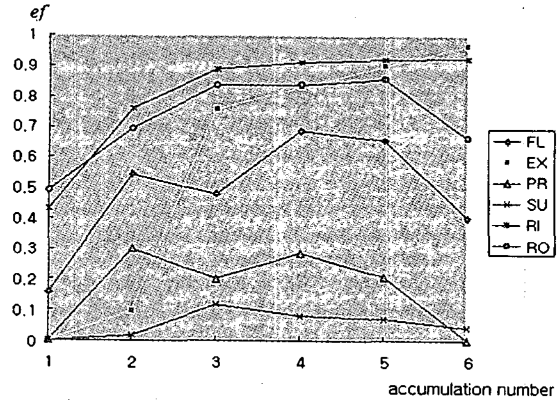

Fig. 8. Value of *ef* according to the procedure of evidence accumulation ; for test signals belonging to *EX* from subject 2.

Table 3. Evidence accumulation procedure; for test signals belonging to *PR* from subject 3.

Parameter \ Motion	*FL*	*EX*	*PR*	*SU*	*RI*	*RO*
IAV	(0.637,0, 0.363,0)	(0.123,0, 0.877,0)	(0.363,0, 0.637,0)	(0.232,0, 0.768,0)	(0.219,0, 0.781,0)	(0.816,0, 0.184,0)
DAMV	(0,0.706, 0.294,0)	(0.345,0, 0.655,0)	(0.251,0, 0.749,0)	(0,0.006, 0.994,0)	(0.095,0, 0.905,0)	(0.331,0, 0.669,0)
VAR	(0.638,0, 0.362,0)	(0.497,0, 0.503,0)	(0.598,0, 0.402,0)	(0.542,0, 0.458,0)	(0,0.611, 0.389,0)	(0.867,0, 0.133,0)
ARC	(0.461,0, 0.539,0)	(0.197,0, 0.803,0)	(0.448,0, 0.552,0)	(0.369,0, 0.631,0)	(0.086,0, 0.914,0)	(0.084,0, 0.916,0)
LCC	(0.089,0, 0.911,0)	(0,0.031, 0.969,0)	(0.370,0, 0.630,0)	(0.406,0, 0.594,0)	(0.028,0, 0.972,0)	(0,0.092, 0.908,0)
ACV	(0.037,0, 0.963,0)	(0,0.857, 0.143,0)	(0.459,0, 0.541,0)	(0.311,0, 0.689,0)	(0.010,0, 0.990,0)	(0,0.349, 0.651,0)
Accumulated Evidence	(0.276,0.044, 0.018,0.662)	(0.106,0.200, 0.032,0.662)	(0.964,0, 0.036,0)	(0.904,0.001, 0.090,0.005)	(0.147,0.380, 0.242,0.231)	(0.583,0.006, 0.009,0.402)

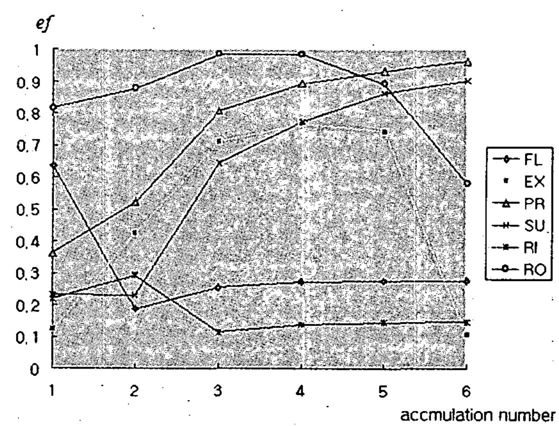

Fig. 9. Value of *ef* according to the procedure of evidence accumulation ; for test signals belonging to *PR* from subject 3.

Table 4. Evidence accumulation procedure; for test signals belonging to *SU* from subject 4.

Motion / Parameter	*FL*	*EX*	*PR*	*SU*	*RI*	*RO*
IAV	(0.702,0, 0.298,0)	(0.575,0, 0.425,0)	(0.354,0, 0.646,0)	(0.270,0, 0.730,0)	(0.038,0, 0.962,0)	(0.603,0, 0.397,0)
DAMV	(0.208,0, 0.792,0)	(0.109,0, 0.891,0)	(0,0.115, 0.885,0)	(0.376,0, 0.624,0)	(0.294,0, 0.706,0)	(0.261,0, 0.739,0)
VAR	(0.695,0, 0.305,0)	(0.621,0, 0.379,0)	(0.571,0, 0.429,0)	(0.252,0, 0.748,0)	(0.245,0, 0.755,0)	(0.640,0, 0.360,0)
ARC	(0.318,0, 0.682,0)	(0.370,0, 0.630,0)	(0.397,0, 0.603,0)	(0.480,0, 0.520,0)	(0,0.137, 0.863,0)	(0.481,0, 0.519,0)
LCC	(0.246,0, 0.754,0)	(0.037,0, 0.963,0)	(0.252,0, 0.748,0)	(0.446,0, 0.554,0)	(0,0.233, 0.767,0)	(0.139,0, 0.861,0)
ACV	(0,0.242, 0.758,0)	(0,0.185, 0.815,0)	(0.268,0, 0.732,0)	(0.545,0, 0.455,0)	(0,0.743, 0.257,0)	(0,0.652, 0.348,0)
Accumulated Evidence	(0.730,0.009, 0.028,0.233)	(0.744,0.016, 0.017,0.169)	(0.804,0.011, 0.081,0.104)	(0.955,0, 0.045,0)	(0.083,0.426, 0.087,0.404)	(0.331,0.031, 0.016,0.622)

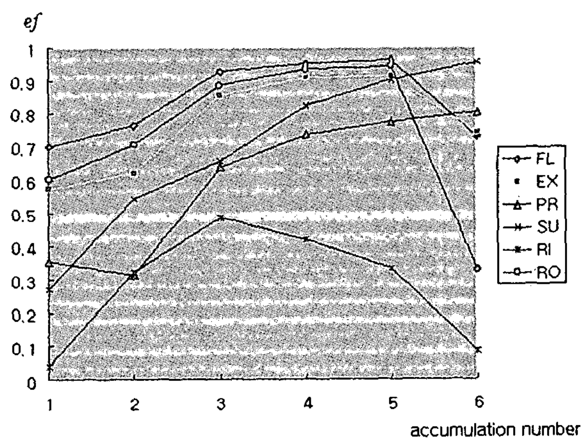

Fig. 10. Value of *ef* according to the procedure of evidence accumulation ; for test signals belonging to *SU* from subject 4.

Table 5. Evidence accumulation procedure; for test signals belonging to *RI* from subject 5.

Motion / Parameter	*FL*	*EX*	*PR*	*SU*	*RI*	*RO*
IAV	(0.427,0, 0.573,0)	(0.295,0, 0.705,0)	(0.427,0, 0.573,0)	(0.294,0, 0.706,0)	(0.428,0, 0.572,0)	(0.650,0, 0.350,0)
DAMV	(0.817,0, 0.183,0)	(0.498,0, 0.502,0)	(0.787,0, 0.213,0)	(0.722,0, 0.278,0)	(0.400,0, 0.600,0)	(0.802,0, 0.198,0)
VAR	(0.704,0, 0.296,0)	(0.567,0, 0.433,0)	(0.609,0, 0.391,0)	(0.663,0, 0.337,0)	(0.421,0, 0.579,0)	(0.842,0, 0.158,0)
ARC	(0.395,0, 0.605,0)	(0,0.041, 0.959,0)	(0.007,0, 0.993,0)	(0.399,0, 0.601,0)	(0.775,0, 0.225,0)	(0.617,0, 0.383,0)
LCC	(0.148,0, 0.852,0)	(0,0.156, 0.844,0)	(0,0.088, 0.912,0)	(0.156,0, 0.844,0)	(0.834,0, 0.166,0)	(0.358,0, 0.642,0)
ACV	(0,0.495, 0.505,0)	(0,0.532, 0.468,0)	(0,1.000, 0,0)	(0,0.193, 0.807,0)	(0.888,0, 0.112,0)	(0,0.279, 0.721,0)
Accumulated Evidence	(0.497,0.008, 0.008,0.487)	(0.321,0.095, 0.058,0.526)	(0,0.047, 0,0.953)	(0.778,0.007, 0.029,0.186)	(0.999,0, 0.001,0)	(0.719,0.001, 0.002,0.278)

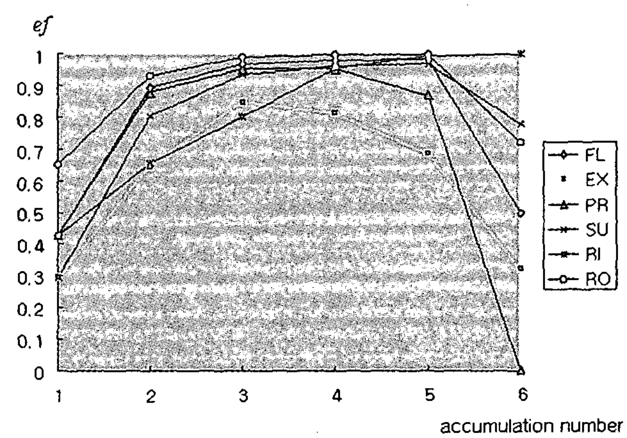

Fig. 11. Value of *ef* according to the procedure of evidence accumulation ; for test signals belonging to *RI* from subject 5.

Table 6. Evidence accumulation procedure; for test signals belonging to *RO* from subject 6.

Motion / Parameter	*FL*	*EX*	*PR*	*SU*	*RI*	*RO*
IAV	(0.274,0, 0.726,0)	(0.226,0, 0.774,0)	(0.565,0, 0.435,0)	(0.522,0, 0.435,0)	(0.570,0, 0.478,0)	(0.603,0, 0.397,0)
DAMV	(0,0.101, 0.899,0)	(0.570,0, 0.430,0)	(0.619,0, 0.381,0)	(0.046,0, 0.954,0)	(0,0.080, 0.920,0)	(0.070,0, 0.930,0)
VAR	(0.439,0, 0.561,0)	(0.183,0, 0.817,0)	(0,0.094, 0.906,0)	(0.658,0, 0.342,0)	(0.615,0, 0.385,0)	(0.137,0, 0.863,0)
ARC	(0.709,0, 0.291,0)	(0.144,0, 0.856,0)	(0.446,0, 0.554,0)	(0.348,0, 0.652,0)	(0.258,0, 0.742,0)	(0.585,0, 0.415,0)
LCC	(0.532,0, 0.468,0)	(0.088,0, 0.912,0)	(0,0.085, 0.915,0)	(0,0.062, 0.938,0)	(0,0.176, 0.824,0)	(0.438,0, 0.562,0)
ACV	(0,0.152, 0.848,0)	(0,0.194, 0.806,0)	(0,0.526, 0.474,0)	(0.018,0, 0.982,0)	(0,0.631, 0.369,0)	(0.665,0, 0.335,0)
Accumulated Evidence	(0.720,0.013, 0.042,0.225)	(0.644,0.039, 0.162,0.155)	(0.357,0.056, 0.036,0.551)	(0.845,0.006, 0.094,0.055)	(0.245,0, 0.034,0.632)	(0.975,0, 0.025,0)

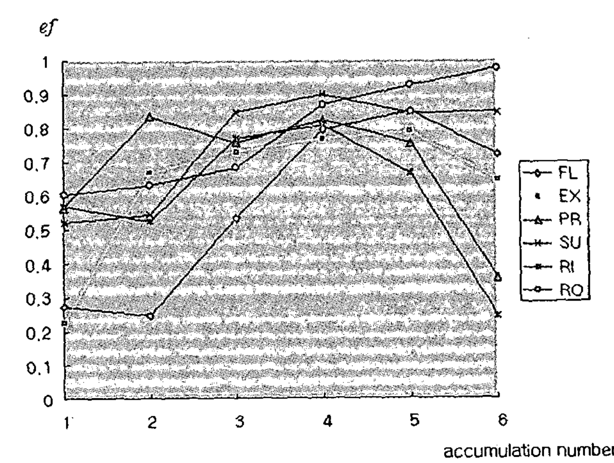

Fig. 12. Value of *ef* according to the procedure of evidence accumulation ; for test signals belonging to *RO* from subject 6.

Table 7. 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).

Method / Motion	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

distances with ARC since the recognition error rates depend on the experimental environments.

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. Also, the separability test showed that ACV is more feasible for EMG pattern classification than the other feature parameters. 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 which are used as inputs to the EMG pattern classifier and to enhance the decision algorithm for preciser pattern recognition with the accumulated evidences.

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