Surface EMG Based Hand Manipulation Identification Via Nonlinear Feature Extraction and Classification

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Abstract—This paper proposes and evaluates methods of nonlinear feature extraction and nonlinear classification to identify different hand manipulations based on surface electromyography (sEMG) signals. The nonlinear measures are achieved based on the recurrence plot to represent dynamical characteristics of sEMG during hand movements. Fuzzy Gaussian Mixture Models (FGMMs) are proposed and employed as a nonlinear classifier to recognize different hand grasps and in-hand manipulations captured from different subjects. Various experiments are conducted to evaluate their performance by comparing 14 individual features, 19 multifeatures and 4 different classifiers. The experimental results demonstrate the proposed nonlinear measures provide important supplemental information and they are essential to the good performance in multifeatures. It is also shown that FGMMs outperform commonly used approaches including Linear Discriminant Analysis, Gaussian Mixture Models and Support Vector Machine in terms of the recognition rate. The best performance with the recognition rate of 96.7% is achieved by using FGMMs with the multifeature combining Willison Amplitude and Determinism.

Index Terms—sEMG recognition, nonlinear feature, FGMMs, manipulation identification.

I. INTRODUCTION

As one of the state-of-the-art techniques to actively control hand prostheses, the surface electromyography (sEMG) has attracted broad interest from both scientific communities and industries. The best-known commercial hand prostheses, such as SensorHand and i-Limb, take advantage of modern processor and motor technologies, become lightweight, fast responsive and easy-to-use. But they are limited to simple motions such as open/close hand and only vision feedback is available [1]. Others prosthetic hands such as Cyberhand [2], Yokoi Hand [3] and the prosthetic hand developed by Shanghai Jiaotong University (SJT-2 hand) [4], are capable of performing complex motions by integrating more electrodes or sensory feedbacks such as vibration and electrotactile. However, to achieve a satisfactory rate for the sEMG signal recognition is still a challenge and is becoming the main focus of the on-going research in rehabilitation and prosthetics. Feature extraction and classifier design have been considered as the two key issues to improve the system accuracy. The former is to define a feature vector from the original sEMG signals, while the latter is to discriminate these feature vectors and group them into different classes.

Various features have been identified both in the time domain, such as integral of sEMG (IEMG), wavelength (WL), variance (VAR), and in the frequency domain, such as cepstral coefficients and Power Spectral Density (PSD). The frequency feature is a short-term feature corresponding to each frequency band, which can be achieved by time-frequency analysis methods such as short-time Fourier transform, wavelet transform and wavelet packet transform [5]–[8]. In [9], autoregressive model (AR) and histogram of sEMG (HEMG) are claimed to be more effective than other six kinds of features including IEMG, WL, VAR, zero crossing (ZC), slope sign change (SSC) and willison amplitude (WAMP). However, Phinyomark et al. proved that WAMP outperforms other features including root mean square (RMS), WL, SSC, HEMG, median frequency, mean frequency, and AR, when they are tested with additive 50 Hz interference at various signal-to-noise ratios [10]. Zhang et al. [8] employed discrete wavelet transform to extract frequency features, which have similar performance with the combined feature IEMG+PSD for six simple hand/arm motions. Six preselected single features and four multi-features have been evaluated and compared in terms of the recognition rate in [11], and the multi-feature, WAV+WL+ZC+SSC, achieved the best performance. In addition, multi-features have also been investigated or evaluated to improve the accuracy for hand motions classification [12], [13].

In terms of classifiers, lots of methodologies have been proposed and applied to process and discriminate sEMG signals, including Neural Networks [12], [14], [15] such as Radial Basis Function Artificial Neural Network [16], statistic approaches such as Hidden Markov Models (HMMs) [17] and Gaussian Mixture Models (GMMs) [12], [18], and fuzzy methods [19]. For example, Naik et al. [20] improved the Back-Propagation Neural Network (BPN) using multi run ICA of sEMG to identify 6 hand gestures and achieved a relatively high classification accuracy of 99%. Each of these 6 hand gestures is only associated with a single flexion, but...
combinations of different flexions and extensions have not been addressed. Oskoei et al. employed Support Vector Machine (SVM) to recognise sEMG signals for myoelectric control applied to upper limb and achieved a recognition rate of around 97% [11]. In addition, a few studies compared several methods [1], [21], [22], e.g., Castellini et al. [1] reported that SVM achieved a higher recognition rate, about 90%, than Neural Networks (NN) and Locally Weighted Projection Regression on five grasp motions, while Liu [23] proposed Cascaded Kernel Learning Machine (CKLM) compared to other classifiers such as k-nearest neighbours, multi-layer NN and SVM. Mahdi et al. employed an adaptive neuro-fuzzy inference system to identify hand motion commands by a hybrid back propagation and a subtractive-clustering algorithm [24]. Subasi compared multi-layer perceptron neural networks (MLPNN), dynamic fuzzy neural network (DFNN) and adaptive neuro-fuzzy inference system (ANFIS) based classifiers in relation to their accuracies in the classification of EMG signals [13]. Tang et al. proposed a cascaded-classifier that divides the classification procedure into several levels and different sEMG features were employed individually in the different levels [25]. The cascaded classifiers are a combination of ordinary classifiers arranged in the cascade to attain higher accuracies. In the cascade, the next classifier is trained with or tested on only the instances where the previous ordinary classifiers are not accurate enough. They have much more complex structures and may potentially increase time and space complexity of training and testing. Their performance also depends on each contained ordinary classifier. However, none of the above has explained why the performance is enhanced. Most of them are more concerned about individual muscle contractions, and the natural movements with combined multiple muscle contractions have not yet been fully tested and addressed. Moreover, there is a lack of consideration of sEMG’s uncertainties arising from the non-stationary nature, different subjects, muscle fatigue, etc.

Since the sEMG signal is a non-stationary signal and stems from a highly nonlinear system embedded in noise [26], it is promising to develop and apply nonlinear approaches to characterise and classify sEMG signals. A recurrence quantification analysis (RQA) was used to analyse the nonlinear dynamical characteristics of sEMG data [27], [28]. With the capability of describing nonlinear nature of short and non-stationary signal corrupted with noise [29], RQA are broadly applied to analyse the physiological data, such as electroencephalogram data [30], [31], fMRI data [32], heart signals [33] and EMG data [34], [35]. It has been proved that RQA methods have potential to detect changes in sEMG due to fatigue [36] and clinical pathology [37].

Based on the previous research [38], this paper investigates nonlinear approaches for sEMG feature extraction and classification using recurrence plot and Fuzzy Gaussian Mixture Models (FGMMs). FGMMs have been proved to be able to fit datasets with curve manifolds and could potentially be employed as a nonlinear classifier with a strengthened performance. This paper employs FGMMs to identify sEMG based natural hand motions in order to control prosthetic hands, with a novel recognition algorithm to improve the recognition efficiency. Different combinations of the linear and nonlinear features are also investigated. Natural hand motions from different subjects, which consist of combinations of finger flexions, extensions, adductions and abductions, are addressed to test various linear/nonlinear features and different classifiers. This paper is organised as follows: Section II describes the recurrence plot and quantification analysis for sEMG feature extraction. Section III presents the modelling and recognition methods using FGMMs. Section IV provides the details of the experiments and demonstrates the performance of the proposed methods. Finally the paper is concluded with concluding remarks in Section V.

II. RECURRENCE PLOT AND QUANTIFICATION ANALYSIS

In the non-linear dynamics theory [39], [40], phase space of the signal needs to be reconstructed, during which time delay methods are usually used to embed a scalar time series into an m-dimensional space:

\[ e_k = (u_k, u_{k+\tau}, \ldots, u_{k+(m-1)\tau}) \]  

where \( k = 1, 2, \ldots, L - (m - 1)\tau \), \( \tau \) is the time delay and \( m \) is the embedding dimension, \( m \geq 2 \). Taken’s theorem states that if the data is infinite and noise-free, the time delay, \( \tau \), can be chosen almost arbitrarily. However, real EMG signals are finite and associated with noises, and the time delay needs to be carefully considered: if \( \tau \) is too small, the reconstructed vector is too close to serve as independent coordinates; if \( \tau \) is too large, the vector becomes independent and loses the connection with each other [41]. The most common method to choose a proper time delay is based on detection of the first local minimum of the mutual information (MI) function, since the first minimum portrays the time delay where the signal \( u_{t+\tau} \) adds maximal information to the knowledge obtained from \( u_t \) [42]. The MI method produces non-linear characteristics of time series, so it is better to estimate time delay than linear autocorrelation functions. For choosing the parameter \( m \), there are a number of different criteria. Cao proposed a method that determines the minimum embedding dimension; it can overcome some shortcomings of false nearest neighbours [43]. In this study, the MI method [42] and Cao’s method [43] are employed to estimate the time delay and the embedding dimension respectively.

Recurrence plots (RP), proposed by Eckmann et al. [44] describes the recurrence property of a deterministic dynamical system, i.e. visualising the time dependent behavior of orbits in a phase space. The key step of RP is to calculate the following matrix:

\[ R_{i,j}(\varepsilon) = \Theta(\varepsilon - ||e_i - e_j||), i, j = 1, \ldots, N \]  

where \( N = L - (m-1)\tau \), \( \varepsilon \) is a predefined cutoff distance, \( || \cdot || \) is the norm (e.g. the Euclidean norm) and \( \Theta(x) \) is a Heaviside function. The phase space vector \( e_i \) can be reconstructed using Takens time delay method, \( e_i = (u_i, u_{i+\tau}, \ldots, u_{i+(m-1)\tau}) \) [40], based on the observations. The cutoff distance \( \varepsilon \) defines a sphere centered at \( e_j \), if \( e_i \) falls within this sphere, i.e. the state is close to \( e_j \), then \( R_{i,j} = 1 \); otherwise \( R_{i,j} = 0 \). The binary values of \( R_{i,j} \) can be simply visualised with the
colours black for 1 and white for 0. Thereby, RP can be considered as a visual inspection of a high dimensional phase space trajectory: in other words, RP indicates the time evolution of a trajectory. In short, RP can describe the characteristics of large-scale and small-scale patterns of a dynamical system [45]. One example of the RP for one sEMG signal can be seen in Fig. 1.

In order to further investigate properties of RP, several measures of complexity that quantify the small-scale structures in RP called recurrence quantification analysis (RQA), have been proposed [45], [46]. Here, we introduced two measure variables that are determinism (DET) and entropy (ENTR). They are based on the recurrence point density and diagonal line structures of the RP. For more details please refer to [47].

The classical measure of RQA is the recurrence rate (RR)

\[
RR(\varepsilon) = \frac{1}{N^2} \sum_{i,j=1}^{N} R_{i,j}(\varepsilon)
\]

(3)

RR is a measure of the density of recurrence points and counts the black dots in the RP.

The frequency distribution of the lengths \(l\) of diagonal structures in the RP is \(P^c(l) = |\{i; i = 1, 2, \ldots, N\}|\). Processes with stochastic behavior cause none or very short diagonals, whereas the deterministic processes cause longer diagonals and less single, isolated recurrence points. Therefore, the ratio of recurrence points on the diagonal structures (of at least length \(l_{\text{min}}\)) to all recurrence points is called the DET, and is introduced as a determinism (or predictability) measure of the system. It is given as:

\[
\text{DET} = \frac{\sum_{i,j}^{N} R_{i,j}(\varepsilon)}{\sum_{i,j}^{N} P^c(l)} = \frac{\sum_{i,j}^{N} R_{i,j}(\varepsilon)}{\sum_{i,j}^{N} P^c(l)}
\]

(4)

where \(l_{\text{min}}\) is the threshold, which excludes the diagonal lines formed by the tangential motion of a phase space trajectory, and in this study we fixed at \(l_{\text{min}} = 2\).

ENTR is the Shannon entropy of the frequency distribution of the diagonal line lengths,

\[
\text{ENTR} = - \sum_{l=l_{\text{min}}}^{N} p(l) \ln p(l)
\]

(5)

where \(p(l) = P(l)/\sum_{l=l_{\text{min}}}^{N} P(l)\). ENTR measures the complexity of the deterministic structure in a dynamical system, and ENTR becomes larger if the structure is more complex.

A parameter specific to the RP is the cutoff distance \(\varepsilon\). If it is too large, almost every point is a neighbour of each other point, which produces a saturation of the RP including irrelevant points; on the contrary, if it is too small, there may be almost no recurrence points, which loses information of the underlying system [47]. Several criteria for the choice of the cutoff distance have been advocated in the literature [48], [49]. One approach uses a fixed number of neighbours, \(N_n\), for every point of the trajectory, called fixed amount of nearest neighbours (FAN) [46]. In this approach, the cutoff distance \(\varepsilon_i\) changes for each state \(\varepsilon_i\) to ensure all columns of the RP have the same recurrence density. Using this neighbourhood criterion, \(\varepsilon_i\) can be adjusted in such a way that the recurrence rate has a fixed predetermined value (i.e. \(RR = N_n/N\) ) [47]; and the RP is invariant under enlarging or reducing of the amplitude of time series.

III. NONLINEAR RECOGNITION METHOD

As one of the most statistically mature methods in pattern recognition and machine learning [50], [51], Gaussian Mixture Models (GMMs) have been successfully implemented to identify high frequency signals such as speech and EMG signals with good performance [18], [52]. In order to equip GMMs with nonlinear fitting capabilities, Fuzzy Gaussian Mixture Models (FGMMs) were proposed in our previous work [53], [54], which were proved to have better fitting performance and a faster convergence speed than conventional GMMs. In this paper, the nonlinear method, FGMMs, will be employed to recognize hand motions including different hand grasps and in-hand manipulations via sEMG signals. In this section, we will firstly revisit the Expectation-Maximization (EM) algorithm for the FGMMs and then propose its recognition method.

A. EM Algorithm for Fuzzy Gaussian Mixture Models

In [53], two types of FGMMs were proposed, including the distance based FGMMs and the probability based FGMMs. In this paper, the distance based FGMMs are chosen and referred as FGMMs, since the performance of the former is better than the latter. The processing of training with FGMMs is summarised as follows.

Let \(X = \{x_1, x_2, \ldots, x_n\}\) be the \(d\) dimensional observed dataset with \(n\) samples; \(k \geq 2\) be the number of the components; \(n\) be the number of the sampling points; \(m > 1\) be the degree of fuzziness; \(\varepsilon > 0\) be a small preset real positive number. The initialisation of FGMMs is achieved by Fuzzy C-Means (FCM). The iteration of the EM algorithm for the FGMMs is:

- E-Step: Compute ‘expected’ classes of all data points for each class.

\[
u_{it} = \left[ \sum_{j=1}^{k} \left( \frac{d_{it}}{d_{ij}} \right)^{\frac{2}{m-1}} \right]^{-1}
\]

(6)

where \(u_{it}\) is the degree of membership of \(x_t\) in the \(i\)th cluster; \(d_{ij}\) is the dissimilarity between point \(x_t\) and \(j\)th
cluster; $d_{ij}$ is the dissimilarity between point $x_i$ and $i$th cluster, which can be archived by
\begin{equation}
  d_{ik}^2 = \begin{cases} 
  \exp\left(\frac{(x_i - \mu_j)^T \Sigma_j^{-1} (x_i - \mu_j)}{2\sigma_1^2}\right) & (|a_i| < \varepsilon) \\
  \frac{n_{i+}}{n_i} p_i(x_i|\theta) & (|a_i| \geq \varepsilon)
  \end{cases}
\end{equation}
(7)
where $\mu_i$ is the mean and $\Sigma_i$ is the covariance matrix of the $i$th Gaussian component; $a_i$ is the weight of $i$th component; $a$ is first parameter of the standard $y = ax^2 + b$ which is used to shape the principle component axis; $p_i(x_i|\theta)$ is the probability density function of point $x_i$ to the $i$th component and it has:
\begin{equation}
  p_i(x_i|\theta) = \left(\frac{1}{\sqrt{2\pi}\Sigma_j}\right)^{-d} \exp\left(-\frac{d^2(x_i, \mu_j)}{2\Sigma_j}\right) \prod_{s=3}^{d} \exp\left(-\frac{d^2(x_i, \mu_j)}{2\Sigma_j}\right) \sum_{i=1}^{d} w_i \end{equation}
(8)
where $l_j(v_{ij})$ is the arc length of the $j$th projected coordinate $z = [z_1, z_2]$, which is transferred from point $x_i$, on the standard curve principle axis; $l_j(v_{ij})$ is the distance between the transferred point $[v_{11}, v_{21}]$ and its projected point $z$. More details about how to get these projected points or transferred points can be found in [53].

- M-Step: Compute Maximum likelihood given the data’s class membership distributions.
If $|a| < \varepsilon$
\begin{equation}
  \mu_i^{new} = \sum_{i=1}^{n} \frac{u_i}{n_i} x_i
\end{equation}
(9)
\begin{equation}
  \Sigma_i^{new} = \sum_{i=1}^{n} \frac{u_i}{n_i} (x_i - \mu_i)^T (x_i - \mu_i) + \frac{Q_i^{new}}{d} (10)
\end{equation}
If $|a| \geq \varepsilon$
\begin{equation}
  (C_i^{new}, T_i^{new}, Q_i^{new}) = LSFM(PCA(X', U_i))
\end{equation}
(11)
$U_i = [u_{i1}, \ldots, u_{im}]$; $PCA()$ is the principal component analysis function for estimating the translation matrix $T_i^{new}$ and rotation matrix $U_i^{new}$. $LSFM()$ is least-squares fitting method for estimating control parameters $C_i^{new} = (a, c)$ which shapes the curve axis with standard curve $y = ax^2 + b$; and the new estimated mean and covariance are:
\begin{equation}
  \mu_i^{new} = \sum_{i=1}^{n} \frac{u_i}{n_i} x_i
\end{equation}
(12)
\begin{equation}
  \Sigma_i^{new} = \sum_{i=1}^{n} \frac{u_i}{n_i} \Sigma_i^{new} (e = 1, 2)
\end{equation}
(13)
\begin{equation}
  \Sigma_i^{new} (3-d) = \sum_{i=1}^{n} \frac{u_i}{n_i} u_i (x_i - \mu_i^{new}) (3-d) (x_i - \mu_i^{new})^T (3-d)
\end{equation}
(14)

The inputs of the FGMMs are the EMG features, number of components $k$, degree of fuzziness $m$ and threshold $\varepsilon$. Then EM algorithm for FGMMs has been utilised to find optimised centers of the components $\mu$, their covariance $\Sigma$ and the control parameters $C, T, Q$, which are the outputs of the FGMMs and will be used in the recognition process. Details to implement the EM algorithm of FGMMs can be found in the appendix in [53]. Fig. 2 gives an example of the trained model via FGMMs, where there are six components to fit the sEMG RMS feature.

B. Recognition
Consider that the FGMMs have $k$ components/patterns. To recognise the testing motion, a similarity function is proposed in (15). The similarity of the testing motion and the trained model of FGMMs is defined by the normalised log-likelihood between the re-sampled testing points and the FGMMs components as:
\begin{equation}
  S_i = \frac{1}{5k} \sum_{j=1}^{5} \log \left( \sum_{i=1}^{k} a_i p_i(x_j \mid \theta_i) \right)
\end{equation}
(15)
where $a_i$ is the mixing coefficient of the $i$th component, if the component’s curvature parameter $a_i < \varepsilon$, the $p(x|\theta)$ will be calculated by:
\begin{equation}
  p(x|\theta) = \frac{1}{(2\pi)^{d/2} \sqrt{|\Sigma|}} \exp\left( -\frac{(x - \mu)^T \Sigma^{-1} (x - \mu)}{2} \right)
\end{equation}
(16)
if its curvature parameter $a_i \geq \varepsilon$, $p(x|\theta)$ is achieved by (8). $x_j$ is the selected points from the testing data $x$ at the time instance of $T_j$, which can be achieved by (17)
\begin{equation}
  T_j = \mu_f + \frac{\eta}{3} [f - \mu_f (j - 1)] + \frac{\gamma}{3} [f - \mu_f (j - 1)]
\end{equation}
(17)
where $T_j$ is the time sampling points for the testing data; $j \in (1, \ldots, 5 \cdot k)$; $\mu_f$ is the time label of the $f$th component center; $f = \frac{(j - 1)}{5}$; the parameters, $\eta$ and $\gamma$, are achieved by (18) and (19):
\begin{equation}
  \eta_j = \begin{cases} 
  2 - [(j - 1) \mod 5] & \text{if } [(j - 1) \mod 5] < 2 \\
  0 & \text{else}
  \end{cases}
\end{equation}
(18)
\begin{equation}
  \gamma_j = \begin{cases} 
  [(j - 1) \mod 5] - 2 & \text{if } [(j - 1) \mod 5] > 2 \\
  0 & \text{else}
  \end{cases}
\end{equation}
(19)
where mod is the module operation to find the remainder of division of one number by another.

The resampling process, shown in Fig. 2, is utilised to reduce the computation cost. The re-sampled points will normally be much fewer than the original data points (reducing data points from \( n \) to \( 5k \), given \( n >> k \)), and thus calculation of the similarity between the testing motion and the trained model will be more efficient. On the other hand, the resampling process locates five re-sampling points around each component, which means the re-sampling points will cover the major distribution of the components even if some of them are relatively small.

IV. EXPERIMENTAL RESULTS

A. Data Collection and Description

The sEMG of 5 forearm muscles shown in Fig. 3, i.e. flexor carpi radialis, flexor carpi ulnaris, flexor pollicis longus, flexor digitorum profundus and extensor digitorum, were measured. To obtain clearer signals, subjects were scrubbed with alcohol and shaved if necessary and then electrodes were applied over the body using the die cut medical grade double-sided adhesive tape. Five electrodes locations were selected according to the musculoskeletal systems related these five muscles and confirmed by muscle specific contractions, which include manually resisted finger flexion, extension and abduction. The EMG capture system using Trigno Wireless Sensors was employed, the resolution is 16 bits and the sampling rate is 4000 Hz. Its size is 37 × 26 × 15 mm and the range of its guaranteed performance is 40 meters. The real time sEMG signals were visualised on a computer screen giving participants feedback to choose electrode locations with stronger sEMG signals.

Eight healthy right-handed subjects including 2 females and 6 males volunteered for the study. Their ages varies from 23 to 40 and the average is 32.5 years old; body height average is 175.5 cm; body mass average is 70 kg. All participants gave informed consent prior to the experiments and the ethical approval for the study was obtained from University of Portsmouth CCI Faculty Ethics Committee. All subjects were trained to manipulate different objects. Participants had to perform ten grasps or in-hand manipulations which are shown in Fig. 4 and the motions are listed as follows

1) Grasp and lift a book using five fingers with the thumb abduction.
2) Grasp and lift a can full of rice using thumb, index finger and middle finger.
3) Grasp and lift a can full of rice using five fingers with the thumb abduction.
4) Grasp and lift a big ball using five fingers.
5) Grasp and lift a disc container using thumb and index finger only.
6) Uncap and cap a marker pen using thumb, index finger and middle finger.
7) Open and close a pen box using five fingers.
8) Pick up a pencil using five fingers, flip it and place it on the table.
9) Hold and lift a dumbbell.
10) Grasp and lift a cup using thumb, index finger and middle finger.

The way to grasp or manipulate objects had been shown to the participants in the demonstration before they performed and every motion lasted about 2 to 4 seconds. Each motion was repeated 10 times. Between every two repetitions, participants had to relax the hands for 2 seconds in the intermediate state that is opening hand naturally without any muscle contraction. These intermediate states were used to segment the motions. Once one motion with ten repetitions was finished, participants had to relax the hand for 2 minutes before the next motion started. This was designed to overcome the effects of muscle fatigue.

B. Feature Extraction and Parameter Setting

Data segmentation is crucial to balance the validity of sEMG features and the real time requirement of the system. It is believed that the time delay between the onset of muscle contraction made by a subject and the corresponding motion in a device should be less than 300 ms for the real time operation; and the minimum interval between two distinct contractions is about 200 ms to contain enough information to estimate a motion state of the hand [11], [55]. In our experiments, we choose the segment length of 300 ms and the increment of 50 ms.

In this paper, various EMG features have been used and compared with the nonlinear features: DET and ENTR, including the time domain features: integrated EMG (IEMG), mean absolute value (MAV), root mean square (RMS), waveform length (WL), zero crossing (ZC), slope sign change (SSC), willison amplitude (WAMP) and frequency domain features: autoregressive coefficients (AR), power spectral density (PSD).

In the reconstruction of the \( m \)-dimensional phase space, the time delay \( \tau \) and the embedding dimension \( m \) of the EMG
epochs are determined by using the MI method and the Cao’s method, and one example could be seen in Fig. 5. From the results of MI and Cao methods applied to all EMG epochs, the optimum values of τ, based on detection of the first local minimum of the MI function, ranged from 2 to 8 samples (mean and standard deviation is 3.68 ± 1.41) for different EMG epochs. So the optimum delay time, τ = 4, is selected for the phase space reconstruction. The optimum embedding dimension m ranged from 5 to 11 (mean and standard deviation are 8.35 ± 1.31) for different EMG segments. Therefore, m = 9 is suitable for the topologically proper reconstruction of the EMG data. The fixed number of neighbours Np is 15 for the every 300 ms EMG segment, and the recurrence rate RR is about 0.05. The performance of every recognition algorithm in the following paper is evaluated by leave-one-subject-out cross-validation.

C. Recognition With One Single Feature

The first experiment was conducted to show the performance comparison of the different single features using a standard recognition algorithm i.e. GMMs. The recognition results are shown in Fig. 6. For the features in the time domain, the WAMP has the highest accuracy while the HIST has the lowest. The MAV, RMS, IEMG and WL have similar performance and ZC has similar performance with SSC. For the frequency features, the AR2 (the second order of the regression model) has the best accuracy and the AR1 (the first order of the regression model) has the lowest. Compared with features in the time domain and the frequency domain, the nonlinear features, DET and ENTR, have lower accuracies, which are around 72 percent. The AR2 has the highest recognition rate, 91.4%, among all features. Fig. 7 presents the confusion matrix for the ten different motions using AR2 feature and GMMs. Motion 1 has the lowest rate of only 71%, while motion 5 and motion 8 have 100% accuracies.

D. Recognition With Multiple Features

It has been proved that the multi-features combining different single features may have better performance than the single features [11], [18]. The objective of the second experiment is to show the performance of multi-features integrating different single ones. The selections of the multi-features are inspired by the work done in [11], [12], and [18]. They are also taken due to their good recognition results and the combinations with poor results are not shown, since the possible combinations could be too many to explain here. In Fig. 8, 19 different combinations have been chosen and their recognition results are compared using GMMs. Due to the similar performance of DET and ENTR, only results of DET have been presented here. From the results, multi-features have overall better and more stable performance compared with the single features, and many of them are above 92%, such as MAV+WL, MAV+DET, and WAMP+DET. These features are better to work together than individually. However,
it is not always true for every combination. For example, AR2 has a recognition rate of 91.4% when used alone, as shown in Fig. 6, but the multi-features, RMS+AR2+DET, have a lower accuracy, which is 89.6%, as displayed in Fig. 8. Among these multi-features, AR6+DET has the lowest recognition rate, and WAMP+DET has the highest rate of 95.7%. When using WAMP alone, the recognition rate is 88.5%, while WAMP+DET achieves 95.75% rate, which is much higher than using WAMP alone. The accuracy of WAMP+DET has improved the best performance from 91.4% achieved by the single features by more than 4 percent. When combined WAMP with other features in the time domain or frequency domain, such as AR2, WL, AR6, MAV, etc., the best rates achieved are 92.6% for WAMP+AR2 and 91.7% for WAMP+WL, which are both lower than combined DET feature. Fig. 9 has presented the confusion matrix for the ten hand motions with the multi-feature WAMP+DET using GMMs.

**E. Recognition With Different Classifiers**

We have investigated the performance comparisons of both single features and multi-features using GMMs. The third experiment is to compare different classifiers, including Linear Discriminant Analysis (LDA), GMMs, Support Vector Machine (SVM) and FGMMs, with the identified best multi-features. LDA is a linear classifier seeking directions in space that has maximum discriminability and has also been employed to analyse biosignals [58]. To have a fare comparison, the recognition process for GMMs is the same as FGMMs which has been proposed in Sec. III-B. The parameter for GMMs and FGMMs is the number of the components ranging from 2 to 20 with increments of one. It is chosen with the best performance for each trained motion model. In this paper, radial basis function for the SVM classifier has been employed, which has been demonstrated to have satisfactory performance in pattern recognition tasks [12], [59]. The parameters for SVM are the kernel parameter ranging from 2 to 20 with increments of one. It is chosen with the best performance for each trained motion model. In this paper, radial basis function for the SVM classifier has been employed, which has been demonstrated to have satisfactory performance in pattern recognition tasks [12], [59]. The parameters for SVM are the kernel parameter ranging from 1 to 10 with increments of one and penalty cost whose range is from 1 to 501 with increments of 50 achieved by using LIBSVM [60] package. These parameters are selected with their best performance.

All the features including the single features and multiple features have been evaluated using different classifiers, and
it was found that the combined feature of WAMP+DET has the best performance for all four classifiers. Since we are more interested in features with better performance, the multi-features with better performance, such as RMS+DET, AR2+DET, MAV+WL, MAV+DET, WL+DET and WAMP+DET, are reported here. The recognition results by different classifiers are shown in Fig. 10. Among all the features and classifiers, FGMMs together with the feature WAMP+DET have the highest recognition rate, which is 96.7%. Fig. 11 presents the box plot of different classifiers for all the selected multi-features and all different subjects. LDA has the lowest accuracies for all the multi-features and the average is 90.77%. GMMs and SVM generally have similar recognition performance and their averages are 93.16% and 93.24% respectively. FGMMs have the highest accuracies, whose average reaches as high as 95.09%. In addition, the confusion matrix of the highest accuracy with WAMP+DET and FGMMs is shown in Fig. 12. The recognition rate of the motion 4 has been improved to 88% though there are still 5% of them which have been mistaken as motion 2. All the other motions have satisfactory results with an average of 97.67%, where the lowest is 93% for motion 2 and motion 6. The experiment results have demonstrated that the nonlinear classifier, FGMM, has better performance than others including GMMs, SVM and LDA, especially with the multi-feature AR2+DET.

The time costs by the single feature extraction and the recognition of different classifiers have also been investigated, as shown in Fig. 13. All of these time costs are estimated in MATLAB running in a 2.3 GHz intel Core i7 computer. The single features are from the multiple features in Fig. 10, where the combined features have relatively good performance. From the results, we can see the DET feature takes the most time cost, which is 11.72 ms. AR2 takes around 2 ms and the others, including RMS, MAV, WL and WAMP, all take less than 1 ms. Compared with the time costs by different classifiers, FGMM takes 2.42 ms to recognise a single motion, which is slightly more than others. According to the above results, the classifier, FGMMs, and the feature, DET+AR2, will take the most computational time to recognise a single motion, and the time cost by the feature extraction and recognition will be around 16.14 ms (11.72+2+2.42). If a window length of 200 ms is considered, FGMM with DET+AR2 feature will take around 220 ms, which will satisfy the time requirement (the time delay is better to be less than 300 ms) of the real prosthetic hand system.

V. CONCLUSION

In this paper, we investigated and evaluated nonlinear approaches to extract sEMG signal features and to identify different types of manipulation motions including different hand grasps and in-hand manipulations. The nonlinear measures DET and ENTR were extracted by the recurrence plot and quantification analysis to represent dynamical characteristics of sEMG during movements. Their performance was compared with a variety of time and frequency features and the comparative results demonstrated that the multi-features,
A. Phinyomark, C. Limsakul, and P. Phukpattaranont, “EMG feature algorithms on prosthetic robotic hands worn by the amputees. In addition, it will also be interesting to test the proposed detection of different hand states in such complex motions show that the proposed nonlinear methods potentially satisfy posed nonlinear features and classifier are essential to improve and the nonlinear classifier FGMMs. It is evident that the proposed nonlinear features and classifier are essential to improve the recognition rate. In addition, the computational cost of the features and classifiers have also been evaluated and the results show that the proposed nonlinear methods potentially satisfy the time requirement of the real-time system. In the future, more complex daily hand motions will be tested and automatic detection of different hand states in such complex motions may also be of great help to improve the system performance. In addition, it will also be interesting to test the proposed algorithms on prosthetic robotic hands worn by the amputees.

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