Effect of VMD decomposition of soleus muscle EMG in SVM classification

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***Abstract*—Electromyography (EMG) is widely used for diagnosis in the field of bio-medical research. The EMG signal from the soleus muscle is utilized in this study to understand the effect of variational mode decomposition (VMD) in signal classification. In this work forward and backward walking in even and uneven surfaces with inclinations of 0^o and 10^o were considered. Ten time domain features were extracted from both raw surface EMG signal, and VMD decomposed EMG signal. Scatter plot of features in all walking condition is analyzed to understand the variation within the scatter group. The features extracted from VMD based components were shown to perform better in accuracy during Support Vector Machines (SVM) classification than the raw signal.**

Keywords—IEMG, Soleus muscle, VMD, SVM

I. INTRODUCTION

Electromyography is used for evaluating and analyzing the electric signal generated during the muscle activity. Nowadays, electromyography (EMG) is a highly recommended tool for muscular disorder diagnosis and clinical research applications[1-2]. The electrical impulse produced by the brain is transferred to the muscles through neurons which controls the muscle activity[3]. Signal variation is the part of work functional or activity change in a muscle. EMG signals has widespread applications in the fields of human-computer interface like prosthesis, electrical orthosis, and virtual control devices[4-5]. In order to apply the EMG signal as the controller of any system, it has to be perfectly classified. Data collection, pre-processing, features extraction, and classification methods are the main four modules in signal analysis and classification[6-7].

Variational mode decomposition based selection procedure should improve the performance of a classifier by promoting the useful information which is hidden in the EMG signal and removes the unnecessary transients[8]. There are two requirements for a good feature selection algorithm:1) there must be a well-defined criterion for judgment on the suitability of the subset of features, and 2) an efficient procedure is essential for searching through the feature space. Mapping a signal to a higher dimensional space helps to differentiate the signals by bringing a hyperplane to separate the different classes. Non-linear mapping done to a certain problem will not work with all cases when choosing a kernel. Structured Support Vector Machines (SVMs) builds these types of kernels[9]. In structured SVM, the signal x undergoes a succession of operations namely convolutions, rectification, normalization, regrouping several times and the filters in convolution operation undergoes learning in order to obtain the representation which is most appropriate for doing classification.

In this work, the surface EMG of soleus muscle were recorded during different walking conditions (forward and backward), and different surface condition (even and uneven) at different inclination(0^o and 10^o). All these conditions produce different signals, the variation in this signal is analyzed with VMD and classified with Support Vector Machines classifier.

This study aims to provide a novel method for accurate identification of EMG signals for varying surface and walking conditions using soleus muscle and also evaluate the EMG features through observation of scatter plots. Made the comparison with SVM classifier to predict the accuracy of the features obtained with and without usingVMD.

II. MATERIALS AND METHODS

The surface electromyography (EMG) signal from soleus muscle was collected during forward and reverse walking on even and uneven surfaces in plane (0^o) and inclined (10^o) conditions. The convertible platform is developed for both even and uneven surfaces, and are covered with 2mm thick polyvinyl foam (PVF) for comfortable walking. The uneven platform is created with four square (15.2×15.2 cm) wooden prisms of varying heights 0, 1.27, 2.54, and 3.81 cm.

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Fifteen healthy male subjects (age: 24 ± 3.1 years, mass 69 ± 9.8 kg and height 170.1 ± 4.7 cm) participated in this study. Signed consent forms were taken from all the subjects who took part in this study. Soleus muscle data are recorded by plugging EKG sensors (EKG-BTA, Vernier USA) to the silver chloride reference electrodes. The position of the electrodes are based on the SENIAM international standards (seniam.org) [10-11]. Data were recorded at 10kHz sampling rate (Butterworth filtered: 20 to 400Hz) with NI USB 6363 data acquisition card through LabVIEW software.

The recorded soleus muscle signal data for all walking conditions is decomposed with VMD. Time-domain based features are extracted from the raw signal and also from the decomposed components of VMD. Both features were classified with SVM classifier to identify the accuracy. The proposed methodology of work as shown in Fig1.

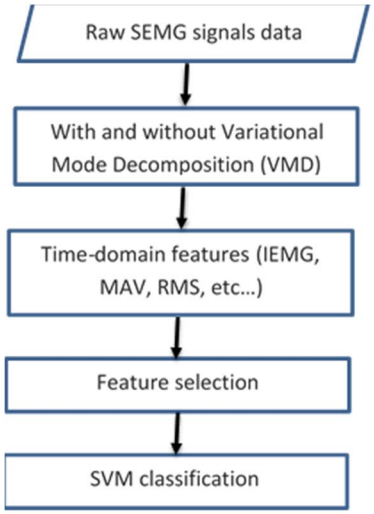


Fig.1 Flow diagram of EMG signal classification and feature extraction using VMD

III. VARIATIONAL MODE DECOMPOSITION

The Variational mode decomposition (VMD) is an adaptive algorithm to decompose a multi-component signal into a combination of discrete set of quasi-orthogonal band-limited intrinsic mode functions (BLIMFs) [12]. Each mode of the signal is assumed to have a compact frequency support around a central frequency. VMD calculates these central frequencies, and the IMFs centered on those frequencies concurrently using an optimization methodology called Alternate Direction Method of Multipliers (ADMM). The original formulation of the optimization problem is continuous in the time domain.

Each mode of the signal is localized on a central frequency which is calculated concurrently by VMD using the following constrained optimization technique [12]:

$$\left.\begin{aligned} &\min_{u_k,\omega_k}\left\{\sum_k \left\|\partial_t\left[\left(\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right)e^{-j\omega_k t}\right]\right\|_2^2,\right. \\ &\left.\text{such that}\ \sum_k u_k = f(t).\right\} \end{aligned} \tag{1}$$

where $f(t)$ is the signal, u is its mode, ω_k is the central frequency, δ is the Dirac distribution depicting the noise tolerance, t is the time script, ∂ is the time derivative, k is the number of IMFs. The central frequencies of all the modes can be initialized as zero.

VMD separated modes of one set of input signals are used in this paper. It shows the low to high oscillating BLIMF distribution for VMD. Thus the high-frequency ones need to be separated in VMD. The modes extracted from VMD is shown in Fig. 2. They depict the compactness of frequency of BLIMFs generated by VMD than IMFs of EMD which shows better decomposition by VMD.

In this study, VMD is performed by setting the number of BLIMFs and number of modes (k) to six due to two reasons. First, the time consumed for higher values of k ($k > 6$) increases without any significant effect in feature extraction. Second, irrespective of the value of k, the features are extracted from high frequency sub-components which are the first few VMD decomposed components. Therefore, in this study the parameters in VMD are taken as k=6 modes, noise-tolerances =0, moderate bandwidth constraint (alpha) = 2000.

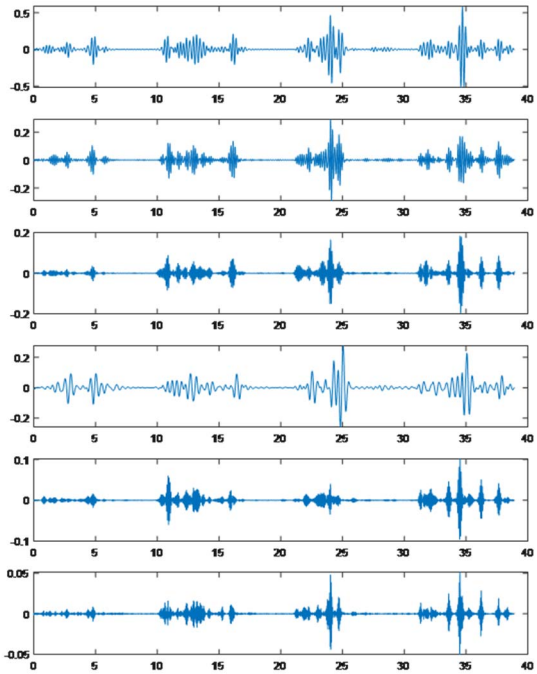


Fig. 2 Example of one set EMG signal is decomposed into six levels using VMD.

IV. TIME DOMAIN FEATURES

The time domain (TD) based features have been extensively applied in the field of medical and engineering research application. Ten features are selected for this study as shown below.

Root mean square (RMS): The RMS value is the square root of the mean value of the squared function of the instantaneous values.

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} X_i^2} \quad (2)$$

Logarithmic root mean square (LR): It is used when the range of target variable is large, and you do not necessarily want to minimize large error values when the predicted and target values are themselves high.

$$LR = \log\left(\sqrt{\frac{1}{n}\sum_{i=1}^{n} X_i^2}\right) \quad (3)$$

Simple square integral (SSI): It is an energy index formulated as the summation of square values of the data amplitude.

$$SSI = \sum_{i=1}^{n} X_i^2 \quad (4)$$

Variance (VAR): It is the average of the squared deviation of a variable. The mathematical definition of VAR is expressed as

$$VAR = \frac{1}{n-1}\sum_{i=1}^{n} X_i^2 \quad (5)$$

Integrated electromyography (iEMG): The most popularly used feature for signal analysis in clinical application. It is defined as the integral of the absolute value of the raw EMG signal.

$$IEMG = \sum_{i=1}^{n} |X_i| \quad (6)$$

Mean absolute value (MAV): It is an average absolute value of EMG signal and very much similar to integrated EMG.

$$MAV = \frac{1}{n}\sum_{i=1}^{n} |X_i| \quad (7)$$

Log detector (LOG): This feature plays a major role in finding muscle contraction force.

$$LOG = e^{\frac{1}{n}\sum_{i=1}^{n} \log(|X_i|)} \quad (8)$$

Waveform length (WL): It is defined as the cumulative length of the EMG waveform.

$$WL = \sum_{i=1}^{n-1} |X_{i+1} - X_i| \quad (9)$$

Zero crossing (ZC): This feature is used to count how many times the signal crosses the baseline axis. X_i and X_{i+1} are the two consecutive samples.

$$ZC = \sum_{i=1}^{n-1} \text{sign}(-X_i * X_{i+1}) \quad (10)$$

Standard Deviation (STDV): It is a statistical feature used in signal processing to quantify the amount of variation of a dataset.

$$STDV = \frac{1}{n}\sum_{i=1}^{n} (X_i - \bar{X})^2 \quad (11)$$

V. SUPPORT VECTOR MACHINE

A support vector machine (SVM) is a machine learning algorithm that analyses data for classification and regression analysis. SVM is a supervised learning method that works on binary classification. An SVM outputs a map of the sorted data with the margins between the two as far apart as possible.

Let $X_1=\{x_1,x_2,\ldots,x_n\}$ be the input and $Y_1=y_1$ be the output label and let Ω_x and Ω_y be their sample spaces. In SVM^{struct}, these can be any spaces, not just integers or real spaces. The feature function ψ is used to map a pair of (x_1, y_1) to a computationally simple form.

$$\Psi = \Omega_x * \Omega_y \quad (12)$$

The classifier described by a vector ω predicts a class by calculating the points where the feature function values are maximum, thus restricting ψ.

$$arg\ max_y\ \omega.\Psi(x,y)$$

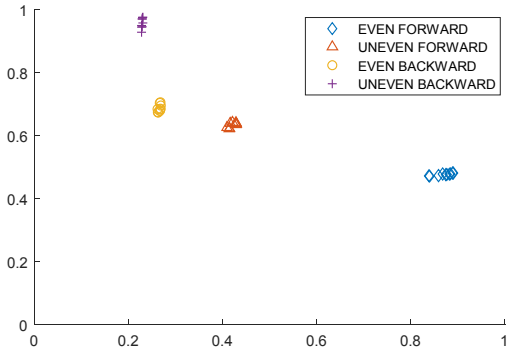
The classifier ω is trained by solving the convex optimization problem:

$$\min_{\omega} \|\omega\|^2 + C\sum_{n} \max_{y}(\Delta(y_n,y) + \omega.(\Psi(x_n,y) - \Psi(x_n,y_n)))$$

Where (x_1, y_1), (x_2, y_2), …, (x_n, y_n) is the training set of only positives and C is the regularisation constant [13]. The extracted features from VMD domain are given as an input to SVM.

VI. RESULT AND DISCUSSIONS

The scatter plot of time domain based features from soleus muscle under different walking conditions is shown to understand the variation within the scatter group. Fig. 3(a-e) shows the scatter plot of RMS, LOG, LR, SSI, and IEMG features, which are extracted from the surface EMG signal. X-axis and y-axis are corresponding normalized data of 0° and 10° inclinations respectively. The entire scatter plots depict a clear separation and compactness which help in characterising the results effectively.



(a)

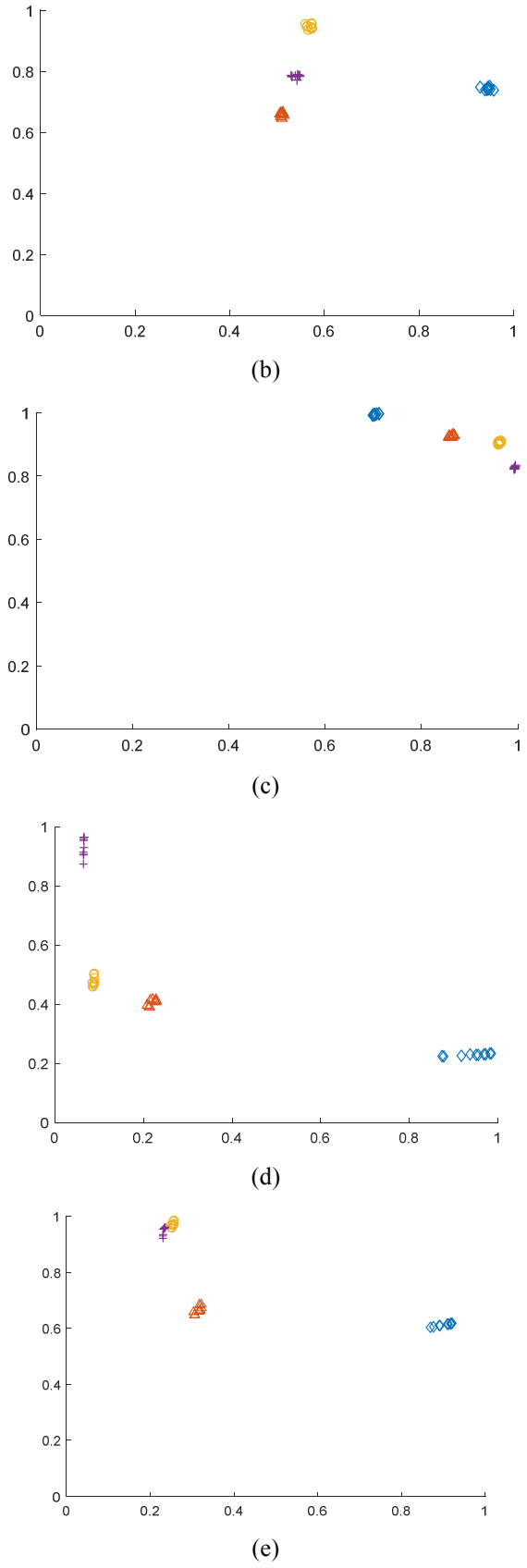


Fig. 3 The comparison between the scatter plots of 0° and 10° inclination surface condition in soleus muscle EMG signal of features (a) RMS, (b) LOG, (c) LR, (d) SSI, (e) IEMG

Zhang et al. studied the vastus medialis muscle group and extract the featutres at different condition like standing, sitting,and gait. And got the classification accuracy of 91.85% for wavelet transform based Singular Value Decomposition approach [14]. Tolambiya et al. analyzed the ensemble activities of postural and focal muscles during a whole body pointing task with SVM, and obtained classification accuracy of 80% [15]. Time-domain based statistical features were extracted from the raw signal and VMD decomposed components of the raw signal. The obtained features were evaluated with SVM by comparing eight different walking conditions (plane even forward walking, plane uneven forward walking, plane even backward walking, plane uneven backward walking, inclined even forward walking, inclined uneven forward walking, inclined even backward walking, inclined uneven backward walking). First, the ten time-domain based raw signal features are characterized with SVM and accuracy percentages are obtained. The selected features produce testing accuracies of 90.11% (for 273 testing samples out of 608 total samples) to 100% (for 154 testing samples out of 608 total samples) in all walking condition. The mean accuracy is obtained as 97.49%, which is reliable in range for the control system design. The time for processing is varying with number of samples and test samples. The time for processing is obtained in the range of 2.781 to 11.245 sec.

TABLE I. DETAILED DESCRIPTION OF THE SAMPLES AND ACCURACY OBTAINED FROM WITHOUT VMD BASED TIME DOMAIN STATISTICAL FEATURE FOR SOLEUS MUSCLE IN ALL WALKING CONDITION.

Percentage of the test sample to Raw sample	Raw sample length	No. of testing samples/ training samples	Number of samples incorrectly classified	Time consumed for processing (sec)	Accuracy obtained (%)
AWC 9%	608	60/548	1	8.326	98.33
AWC 18%	608	110/498	3	9.431	97.27
AWC 25%	608	154/454	0	11.245	100
AWC32 %	608	197/411	3	6.225	98.48
AWC41 %	608	251/357	13	10.081	94.82
AWC 44%	608	273/335	27	7.821	90.11
AWC 49%	608	300/308	2	5.355	99.93
AWC 53%	608	324/284	5	4.473	98.46
AWC 58%	608	358/250	5	2.781	98.60
AWC 64%	608	393/215	4	6.866	98.98

Next, the same procedure is repeated for features from the VMD domain signal components. The selected features produce testing accuracies of 98.1% (for 158 testing samples out of 608 total samples) to 100% (for 57 and 105 testing samples out of 608 total samples) in all walking condition. The mean accuracy obtained with VMD is 99.32%, which is more than the first case (without VMD). The time for processing is obtained in the range of 7.851 to 17.962 sec. Time consumed

for processing is larger compared with raw signal (without VMD), because the time-domain features are extracted from the six modes of VMD obtained components.

TABLE II. DETAILED DESCRIPTION OF THE SAMPLES AND ACCURACY OBTAINED FROM VMD BASED TIME-DOMAIN STATISTICAL FEATURE FOR SOLEUS MUSCLE

Percentage of the test sample to Raw sample	Raw sample length	No. of testing samples/ training samples	Number of samples incorrectly classified	Time consumed for processing (sec)	Accuracy obtained (%)
AWC 9 %	608	57/551	0	16.791	100
AWC 17%	608	105/503	0	17.250	100
AWC26 %	608	158/450	3	9.525	98.1
AWC 32%	608	197/411	1	17.882	99.49
AWC 37%	608	229/379	2	12.082	99.13
AWC 45%	608	277/331	3	12.293	98.92
AWC 49 %	608	300/308	1	7.851	99.67
AWC 52 %	608	317/291	3	12.041	99.05
AWC 58%	608	354/254	2	17.962	99.44
AWC 63%	608	387/221	2	13.26	99.48

VII. CONCLUSIONS

The proposed work investigates the effect of EMG signal decomposition in VMD domain from soleus muscle under different walking conditions. A comparison was performed with time domain features extracted from the raw EMG signal and also VMD decomposed components of the raw signal. The effect of selected features for classification is analyzed with scatter plots. The VMD based features were shown to provide highest level of accuracy for all test samples when compared to the features obtained from the raw signal without decomposing with VMD. Time consumed for the classification is more in feature extraction with VMD decomposed signal than the raw signal due to the large size of input data.

REFERENCES

[1] Canal, Mehmet Rahmi. "Comparison of wavelet and short time Fourier transform methods in the analysis of EMG signals." Journal of medical systems 34, no. 1 (2010): 91-94.

[2] Oskoei, Mohammadreza Asghari, and Huosheng Hu. "Myoelectric control systems—A survey." Biomedical Signal Processing and Control 2, no. 4 (2007): 275-294.

[3] Ethier, Christian, Emily R. Oby, M. J. Bauman, and Lee E. Miller. "Restoration of grasp following paralysis through brain-controlled stimulation of muscles." Nature 485, no. 7398 (2012): 368.

[4] Delis, Alberto L., Joao LA Carvalho, Adson F. Da Rocha, Renan U. Ferreira, Suélia S. Rodrigues, and Geovany A. Borges. "Estimation of the knee joint angle from surface electromyographic signals for active control of leg prostheses." Physiological measurement 30, no. 9 (2009): 931.

[5] Hussain, M. S., Mamun Bin Ibne Reaz, Faisal Mohd‐Yasin, and Muhammad I. Ibrahimy. "Electromyography signal analysis using wavelet transform and higher order statistics to determine muscle contraction." Expert Systems 26, no. 1 (2009): 35-48.

[6] Boostani, Reza, and Mohammad Hassan Moradi. "Evaluation of the forearm EMG signal features for the control of a prosthetic hand." Physiological measurement 24, no. 2 (2003): 309.

[7] Zecca, Micera, Silvestro Micera, Maria C. Carrozza, and Paolo Dario. "Control of multifunctional prosthetic hands by processing the electromyographic signal." Critical Reviews™ in Biomedical Engineering 30, no. 4-6 (2002).

[8] Zardoshti-Kermani, Mahyar, Bruce C. Wheeler, Kambiz Badie, and Reza M. Hashemi. "EMG feature evaluation for movement control of upper extremity prostheses." IEEE Transactions on Rehabilitation Engineering 3, no. 4 (1995): 324-333.

[9] Cristianini, Nello, and John Shawe-Taylor. An introduction to support vector machines and other kernel-based learning methods. Cambridge university press, 2000.

[10] Fattorini, L., A. Tirabasso, A. Lunghi, R. Di Giovanni, F. Sacco, and E. Marchetti. "Muscular forearm activation in hand-grip tasks with superimposition of mechanical vibrations." Journal of Electromyography and Kinesiology 26 (2016): 143-148.

[11] Mika, Anna, Łukasz Oleksy, Piotr Mika, Anna Marchewka, and Brian C. Clark. "The influence of heel height on lower extremity kinematics and leg muscle activity during gait in young and middle-aged women." Gait & posture 35, no. 4 (2012): 677-680.

[12] Dragomiretskiy, Konstantin, and Dominique Zosso. "Variational mode decomposition." IEEE transactions on signal processing 62, no. 3 (2014): 531-544.

[13] Nguyen, Nam, and Yunsong Guo. "Comparisons of sequence labeling algorithms and extensions." In Proceedings of the 24th international conference on Machine learning, pp. 681-688. ACM, 2007.

[14] Zhang, Yi, Peiyang Li, Xuyang Zhu, Steven W. Su, Qing Guo, Peng Xu, and Dezhong Yao. "Extracting time-frequency feature of single-channel vastus medialis EMG signals for knee exercise pattern recognition." PloS one 12, no. 7 (2017): e0180526.

[15] Tolambiya, Arvind, Elizabeth Thomas, Enrico Chiovetto, Bastien Berret, and Thierry Pozzo. "An ensemble analysis of electromyographic activity during whole body pointing with the use of support vector machines." PloS one 6, no. 7 (2011): e20732.