Neighborhood Components Analysis in sEMG Signal Dimensionality Reduction for Gait Phase Pattern Recognition

Jirapong Manit
Institute of Field Robotics
King Mongkut's University of Technology Thonburi
Bangkok, Thailand
Email: 52432302@study.fibo.kmutt.ac.th

Prakarnkiat Youngkong
Institute of Field Robotics
King Mongkut's University of Technology Thonburi
Bangkok, Thailand
Email: youngkong@fibo.kmutt.ac.th

***Abstract*—Dimensionality reduction technique is an essential method for sEMG signal pattern recognition and classification, especially for real-time application such as prosthesis control. This technique can reduce the high dimension extracted feature into a lower dimension space feature which help the classifier works more properly. This paper presents an application of a dimensionality reduction technique called neighborhood components analysis (NCA). We evaluate the efficiency of NCA by comparing its class separability and the classification accuracy with other three algorithms: principle component analysis (PCA), linear discriminant analysis (LDA) and local preserving projection (LPP). The result shows that NCA outperform other algorithm in the class separability, and its classification accuracy is also slightly higher.**

***Index Terms*—neighborhood components analysis (NCA), surface electromyography (sEMG), myoelectric, gait phase, pattern recognition, dimensionality reduction**

I. Introduction

Surface electromyography (sEMG) is a method to record the myoelectric signal which are formed by physiological variations in the state of muscle fiber membranes. In the field of engineering, sEMG signal is widely used in many studies such as intelligent prosthetic and exoskeleton control input [1]–[4], because of its ability in direct inflecting user's movement intention. Therefore, improving the performance of sEMG pattern recognition is theory essential for real-time applications. Many schemes and techniques were introduced to increase the system accuracy and reduce the computational time [4]–[10]. One widely used technique that makes the recognition more effective is dimensionality reduction. It is implemented when transformation of high-dimension into a lower dimension space is required, while significant characteristics of the original feature are still preserved. On the other hand, feature projection would make separability of each class higher. And, the system classifier can work more properly. There are several dimensionality reduction techniques which are introduced to handle sEMG signals. K. Englehart, B. Hudgins *et al*. [8] had defined the classification problem into three sections consisting of feature extraction, dimensionality reduction and classification. For the dimensionality reduction, principle components analysis (PCA) was selected to perform a linear feature projection. Their research showed that the application of PCA was critical to the success of the time-frequency based feature sets, and that PCA was superior to other forms of dimensionality reduction. A combination method between PCA and self-organizing feature map (SOFM) was presented in [11]. Eight classes of the input feature were first projected by PCA into a 2-dimension space and then was enhanced separation margin by SOFM. It is quite obvious that the final projected features have more separability than only PCA projected. According to [2], PCA was compared with other three projection techniques; linear discriminant analysis (LDA), nonlinear discriminant analysis (NLDA) and self-organizing feature map (SOFM) by using Sammon's stress (E) and Fisher's index (J) as two separability measures. The final result showed that PCA was outperformed by LDA projection with 0.976 of E and 25345.8 of J. However, [12] shows that there are some drawbacks of LDA when the number of samples per class is small or the training data non-uniformly sample the underlying distribution. In a real situation, a suitable number of the sample data is unknown.

A novel supervised non-parametric dimensionality reduction method called neighborhood components analysis (NCA) was proposed by Jacob G. *et al* [13]. It is a method for learning a Mahalanobis distance measure, used in the k-nearest neighborhood classification algorithm. And, it is capable of learning a low-dimensional linear embedding of labeled data. Comparing with two classical algorithms, PCA and LDA, the NCA transformation gives higher class separability than the others.

In this paper, we present an application of the NCA for gait phase sEMG signal dimensionality reduction comparing with the other three projection techniques: PCA LDA, and LPP. Two main gait phases, namely stance phase and swing phase, are considered in this study. To evaluate the efficiency of each algorithm, two class separability measures: Thornton's separability index (IS) and direct class separability measure ($DCSM$), in [14] were applied. Finally, the result of

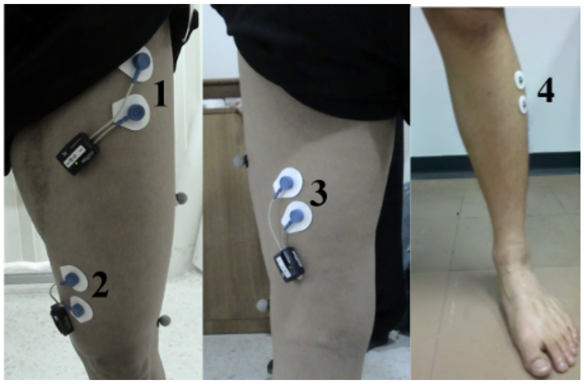


Fig. 1. Electrodes Location: (1) rectus femoris, (2) biceps femoris, (3) medial gastrocnemius and (4) tibialis anterior

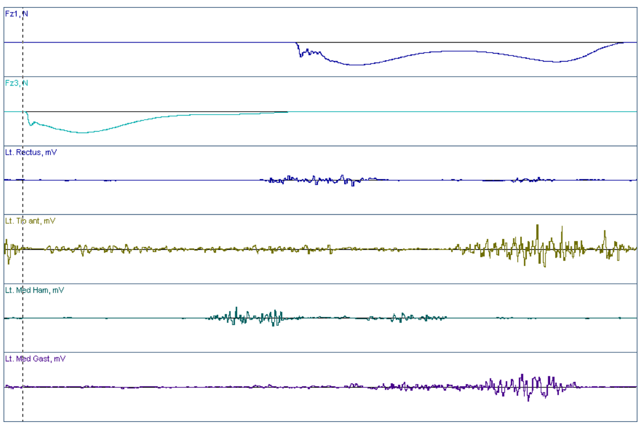


Fig. 2. Raw sEMG signals of a single left leg walk cycle with two force plate signals. The top two signal on the graph are the force signals.

classification accuracy is shown via the support vector machine (SVM).

II. Methodology

A. EMG Data Acquisition

The high-end wireless EMG signal recording equipment, ZeroWire from Noraxon, is used in this study. sEMG signals are collected from four muscles on both legs; namely rectus femoris, biceps femoris, medial gastrocnemius and tibialis anterior, with 16-bit data and sampling rate of 1500 Hz. The bandpass filter between 10 to 1000 Hz is applied to the signals. The Ag-AgCl electrodes were attached on legs of a subject as shown in Fig. 1. Five healthy male subjects aged between 20 to 26 years old were instructed to walk bare foot at a comfortable pace 5 times repeatedly. The walk path is a 10 meters hard floor implanted with three force plates which are used to identify the interval of swing phase and stance phase.

The raw sEMG signals are labeled manually accordingly to the force signal. Stance phase interval will first start when a signal from a force plate appears and stop when value of the force signal is zero. Figure 2 illustrates sEMG signals collected from a gait cycle. The classes of stance- and swing-phase signals are marked as 1 and -1, respectively. The whole data of each class is divided into two equal sets, a training set and a testing set for the classification.

B. Feature Extraction

While using the raw sEMG signal is very difficult to classify movements or activities of users, various types of feature extraction and their combination are introduced to make the sEMG pattern classification more reliable [5], [8], [15]–[17] . In this study, we will mention only the time-domain feature extractions.

Mean Absolute Value (MAV) is one of the most popular time-domain feature extraction for sEMG signal classification. It is the average of the absolute value of sEMG signal which shows the muscle contracting amplitude. The MAV is defined as

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{1}$$

where N is length of the signal in a segment and x_i is a sEMG signal value of the i^{th} sample.

Waveform Length (WL) is the cumulative length of the waveform over the time segment. WL is related to the waveform amplitude, frequency and time. It is given by

$$WL = \frac{1}{N}\sum_{i=1}^{N-1}|x_{i+1} - x_i| \tag{2}$$

Variance (VAR) uses the power of the sEMG signal as a feature. Generally, the variance is the mean value of the square of the deviation, which can be calculated by

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N}{x_i}^2 \tag{3}$$

Here, we remark that the average value of sEMG signal (x_i) is approximately zero

Root Mean Square (RMS) is modeled as amplitude modulated Gaussian random process whose RMS is related to the constant force and non-fatiguing contraction. It can be expressed as

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2} \tag{4}$$

Willison Amplitude (WAMP) is a number of times that the difference between sEMG signal amplitude among two adjacent segments exceeds a predefined threshold. It is related to the firing of motor unit action potentials (MUAP) and the muscle contraction level. The definition of WAMP is

$$\begin{gathered} WAMP = \sum_{i=1}^{N-1} f(|x_i - x_{i+1}|) \\ f(x) = \begin{cases} 1, \text{if } x \geq threshold \\ 0, \text{otherwise} \end{cases} \end{gathered} \tag{5}$$

Generally, the $threshold$ value is suggested to be in a range of 10 and 100 mV, depending on the setting of the gain value of instrument [17]. In this study, the the $threshold$ is chosen to be 30 mV.

MAV, WL, VAR and RMS are calculated in a segment of sEMG signal. According to the real-time control scheme presented in [7], the performance of the analysis window length (T_a) between 32 ms to 256 ms is not significantly different. Thus, the T_a and window sliding time are selected to be 64 ms and 32 ms, respectively. And, the sample number in a calculating segment (N) is 96.

C. Dimensional Reduction

After the feature extraction, each feature vector will be reduced its dimension into 2 using four algorithms separately for faster computational time and less complexity in the classification. The number of feature dimension depends on the number of sEMG channels. Therefore, these features consist of 4-dimensional vectors.

Neighborhood Components Analysis (NCA): This algorithm is a novel method proposed by J. Goldberger et al. for learning a Mahalanobis distance measure used in the k-nearest neighborhood (KNN) classification algorithm. The Mahalanobis distance matrices can be represented by symmetric positive semi-definite matrices and estimated using inverse square roots. Instead of estimating the actual leave-one-out classification error of KNN, a more effective measure by using a differentiable cost function based on a stochastic neighbor assignment in the transformed space was introduced. Define the probability that a point i selects another point j as its neighbor (p_{ij}) as

$$p_{ij} = \frac{\exp\left(-\left\|Ax_i - Ax_j\right\|^2\right)}{\sum_{k \neq i} \exp\left(-\left\|Ax_i - Ax_k\right\|^2\right)} \quad , \quad p_{ii} = 0 \qquad (6)$$

where A is a linear transformation matrix. The objective of NCA is to maximize the *expected number of points correctly classified* under the scheme

$$f(A) = \sum_i \sum_{i \in C_i} p_{ij} = \sum_i p_i \qquad (7)$$

D. Class Separability Measures

Thornton's separability index (SI): This is a measure of the degree to which inputs associate with the same output cluster together. It is shown in [18] to be an effective measure of class separability. The output value of SI is range between 0 and 1. In the case that each class is in a well-separated cluster, the output will be close to 1. And, the index will approach to 0 when the clusters move closer. The SI is defined as:

$$SI = \frac{\sum_{i=1}^{n} \left(f(x_i) + f(x_i') + 1\right) \bmod 2}{n} \qquad (8)$$

where f is a binary target function, x_i' is the nearest neighbor of x_i and n is the number of points.

Direct Class Separability Measures (DCSM): This measure is a more informative measure for separability than the class scatter matrices approach [14]. It directly measures how compact each class is as compared to how far it is from the other class by using the within class distance (S_w) and between class distances (S_b). $DCSM$ is calculated from:

$$DCSM = [S_b - S_w] \qquad (9)$$

$$S_w = \sum_{i_1=1}^{ni} \sum_{i_2=1}^{ni} \left\|x_{i_1} - x_{i_2}\right\| \qquad (10)$$

$$S_b = \sum_{i=1}^{ni} \sum_{j=1}^{nj} \left\|x_i - x_j\right\| \qquad (11)$$

where ni, nj are the numbers of instances in class i, j respectively and x_i, x_j are the instances. Denoting, the stance-phase and stance-phase as S_{w+} and S_{w-}, respectively. The result of $DSCM$ can be interpreted that if for one dataset, $S_b < S_{w-}$ and $S_b > S_{w+}$, then the scattering of the swing-phase class is more than the scattering between swing-phase class and the stance-phase class. Furthermore, the swing-phase class overlaps the stance-phase class.

Ploting between the $DSCM$ against SI can show more separabirity information of the transformed feature. When a slope of the relationship between $DCSM$ and SI of both classes are the same, the classes are easily separated. And, if the slope are different, one class is overlapping the other.

E. Pattern Classification

The classifier we use in this study is a binary support vector machine (SVM) which is a powerful classifier. Fast computational time and ability to handle non-linearity of SVM are advantages which are suitable for sEMG signal classification [9]. Radial basis function (RBF) in (12) with the $\gamma = 1/2\sigma^2$ is used as the kernel function of SVM.

$$k(x_i, x_j) = \exp(-\gamma \left\|x_i - x_j\right\|^2) \qquad (12)$$

The SVM is first trained by the training data set, then tests the system accuracy by another testing set.

III. Result and Discussion

The performance of each dimensionality reduction algorithm is compared by two values: class separability and classification accuracy. The assumption is that, a class which has more separability should get more accuracy in the classification.

Class separability

As showing in Fig. 3, all extracted features are reduced from 4-dimensional into 2-dimensional space. The class separability can reveal the information of how easy these data sets can be separated. Considering just the SI in Fig. 4, it can be seen that the separability of NCA in the MAV RMS and WAMP is higher than those from other algorithms. Furthermore, the

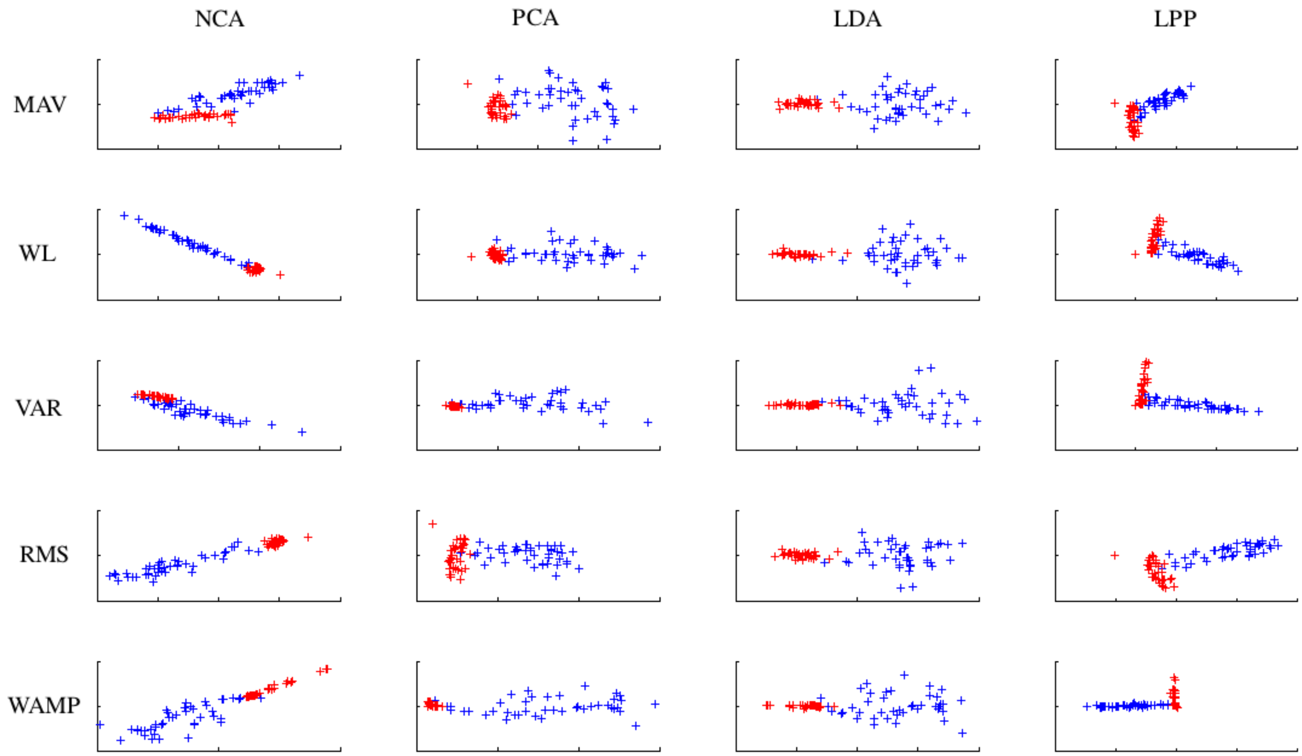


Fig. 3. The 2-dimension projected features by NCA, PCA, LDA and LPP.

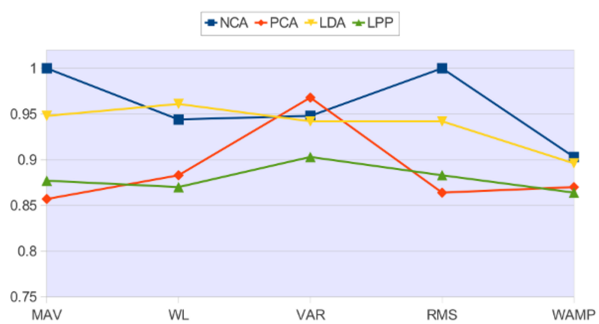
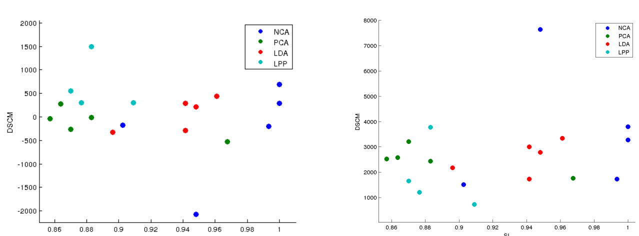


Fig. 4. Thornton's separability index (SI) of each algorithm.



(a) S_{w+} vs. SI (b) S_{w-} vs. SI

Fig. 5. $DCSM$ vs. SI

MAV and RMS features projected by NCA can gain the maximum score of SI. This means the stance-phase and swing-phase class of these two data sets are completely separated. So, MAV and RMS are good feature extractions for the NCA system. LDA, PCA and LPP get less average score than NCA. Regarding to the variation of SI for each feature extraction, the dimensionality reduction algorithms are much effective to MAV, WL VAR and RMS. The small variation of SI in WAMP can be explained that it is not much different for each algorithm to be applied with WAMP.

To investigate more information, the data plot between $DSCM$ of stance-phase class (S_{w+}) versus SI and $DSCM$ of swing-phase class (S_{w-}) versus SI are shown in Fig. 5. The slopes of both two graphs are quite the same which means that the stance-phase class and the swing-phase class are easily separated. In Fig. 5, the outlier of NCA in the graph is the value of WL. This result can be compared with the projected feature plot in Fig. 3 that there are more overlapping data point than other features. Even though, the slope of LDA is more similar to each other than the NCA, and it has no outlier. NCA is more easily separable than LCA, bacause three right most data points on both graph in Fig. 5 are the NCA. Therefore, the dimensionality reduction technique that can gain most class separability is the NCA.

Classification accuracy

As shown in Fig. 6, every feature from all dimensionality reduction techniques can give the accuracy more than 90 %. The most accurate system is the projected feature of MAV from NCA, with the result of 99.69% accuracy. And, the second most accurate system is also the RMS from NCA.

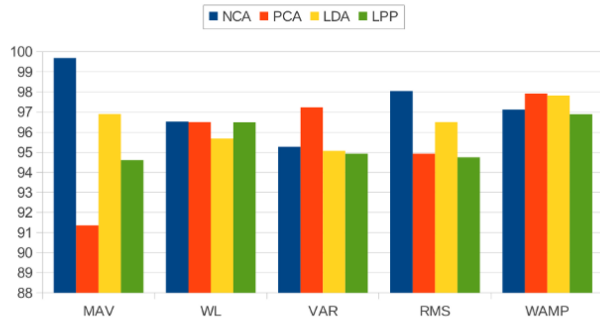


Fig. 6. Classification accuracy of each projected feature

TABLE I
AVERAGE CLASSIFICATION ACCURACY AND THORNTON'S SEPARABILITY INDEX FOR EACH DIMENSIONALITY REDUCTION ALGORITHM

	NCA	PCA	LDA	LPP
Accuracy	97.332 %	95.592 %	96.400 %	95.536 %
IS	0.959	0.888	0.938	0.879

According to the Table I, it is seen that class separability of the sEMG data set relates to the classification accuracy.

IV. CONCLUSION

We have investigated an application of NCA to reduce the dimension of the gait phase sEMG signals and make the classification system gains more accuracy. The results show that NCA yields better class separability. Furthermore, the average classification accuracy of the transformed features by NCA is higher than PCA, LDA and LPP. Therefore, NCA can be used as the dimensionality reduction technique for sEMG signal classification system better than the conventional techniques.

The future work on this study is to investigate on the computational time on the real system.

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REFERENCES

[1] A. Delis, J. de Carvalho, G. Borges, S. de Siqueira Rodrigues, I. dos Santos, and A. da Rocha, "Fusion of electromyographic signals with proprioceptive sensor data in myoelectric pattern recognition for control of active transfemoral leg prostheses," in *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE*, sept. 2009, pp. 4755 –4758.

[2] J.-U. Chu, I. Moon, Y.-J. Lee, S.-K. Kim, and M.-S. Mun, "A supervised feature-projection-based real-time emg pattern recognition for multifunction myoelectric hand control," *Mechatronics, IEEE/ASME Transactions on*, vol. 12, no. 3, pp. 282 –290, june 2007.

[3] K. Momen, S. Krishnan, and T. Chau, "Real-time classification of forearm electromyographic signals corresponding to user-selected intentional movements for multifunction prosthesis control," *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, vol. 15, no. 4, pp. 535 –542, dec. 2007.

[4] R. Khushaba, A. Al-Ani, and A. Al-Jumaily, "Orthogonal fuzzy neighborhood discriminant analysis for multifunction myoelectric hand control," *Biomedical Engineering, IEEE Transactions on*, vol. 57, no. 6, pp. 1410 –1419, june 2010.

[5] K. Englehart, B. Hudgin, and P. Parker, "A wavelet-based continuous classification scheme for multifunction myoelectric control," *Biomedical Engineering, IEEE Transactions on*, vol. 48, no. 3, pp. 302 –311, march 2001.

[6] J.-U. Chu, I. Moon, and M.-S. Mun, "A real-time emg pattern recognition based on linear-nonlinear feature projection for multifunction myoelectric hand," in *Rehabilitation Robotics, 2005. ICORR 2005. 9th International Conference on*, june-1 july 2005, pp. 295 – 298.

[7] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *Biomedical Engineering, IEEE Transactions on*, vol. 50, no. 7, pp. 848 –854, july 2003.

[8] K. Englehart, B. Hudgins, P. A. Parker, and M. Stevenson, "Classification of the myoelectric signal using time-frequency based representations," *Medical Engineering & Physics*, vol. 21, no. 6-7, pp. 431 – 438, 1999.

[9] M. Oskoei and H. Hu, "Support vector machine-based classification scheme for myoelectric control applied to upper limb," *Biomedical Engineering, IEEE Transactions on*, vol. 55, no. 8, pp. 1956 –1965, aug. 2008.

[10] J. Manit and P. Youngkong, "Combination of surface emg signal features for gait phase detection," in *The Seventh Asian Conference on Computer-Aided Surgery*, August 2011.

[11] J.-U. Chu, I. Moon, S.-K. Kim, and M.-S. Mun, "Control of multifunction myoelectric hand using a real-time emg pattern recognition," in *Intelligent Robots and Systems, 2005. (IROS 2005). 2005 IEEE/RSJ International Conference on*, aug. 2005, pp. 3511 – 3516.

[12] A. Martinez and A. Kak, "Pca versus lda," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 23, no. 2, pp. 228 –233, feb 2001.

[13] J. Goldberger, S. Roweis, G. Hinton, and R. Salakhutdinov, "Neighbourhood components analysis," in *Advances in Neural Information Processing Systems 17*. MIT Press, 2004, pp. 513–520.

[14] L. Mthembu and J.Greene, "A comparison of three class separability measures," in *Fifteenth Annual Symposium of the Pattern Recognition Association of South Africa*, november 2004, pp. 63–67.

[15] H. Hermens, T. B. van, C. Baten, W. Rutten, and H. Boom, "The median frequency of the surface emg power spectrum in relation to motor unit firing and action potential properties," *Journal of Electromyography and Kinesiology*, vol. 2, no. 1, pp. 15–26, 1992.

[16] H. H. D. Tkach and T. A. Kuiken, "Study of stability of time-domain features for electromyographic pattern recognition," *Journa of Neuroengineering and Rehabilitation*, vol. 7, no. 21, may 2010.

[17] M. Zardoshti-Kermani, B. Wheeler, K. Badie, and R. Hashemi, "Emg feature evaluation for movement control of upper extremity prostheses," *Rehabilitation Engineering, IEEE Transactions on*, vol. 3, no. 4, pp. 324 –333, dec 1995.

[18] J.Greene, "Feature subset selection using thornton's separability index and its applicability to a number of sparse proximity-based classifiers," in *Twelfth Annual Symposium of the South African Pattern Recognition Association*, 2001.