Time-frequency Features for sEMG Signals Classification

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Keywords: Time-frequency Analysis, Features Extraction, Prosthetic Arm, sEMG, Hand Gesture.

Abstract: This paper proposes a new approach for the identification of hand movements in order to control prosthetic hand. sEMG signals were used to identify movements by using two time frequency transforms: Short Time Fourier Transform and Stockwell transform. Then, we apply Singular Value Decomposition (SVD) to decrease the features dimension and to form the final features' vector. These extracted features were used by two kinds of classifiers: K nearest neighbours and linear discriminant analysis. Finally, we numerically study these methods on a database of 10 subjects and 17 hand gestures.

1 INTRODUCTION

Prosthetic hand is an important help for people who lost their upper limb in order to restore their biological hand functionality.

Recognizing multiple hand movements depending on sEMG signals coming from electromyography sensors is a challenging task especially with adding more movements to study which makes classification rate worse significantly.

Surface electromyography signal (sEMG) is a bio-electrical signal generated along with skeletal muscles activities, and it differs according to movement controlled by these muscles, and that makes this signal very useful in many applications as human-machine interaction, rehabilitation of handicapped people, and controlling limb prosthetic (Raez et al., 2006).

The sEMG signal has been widely studied in the literature. However, it is still difficult to apply it to control prosthetic arm. That comes from the complexity in human hand movements which has more than 20 degrees of freedom and from the non-stationary nature of the signal. The sEMG amplitude ranges from 50 µV to 10 mV and frequency spec-trum lies between 20 Hz and 500 Hz (Meselmani et al., 2016).

Recording sEMG is performed by placing several electrodes on the skin, and different studies were done to obtain better results in this area. Over the past decades, different electrode placement strategies have been investigated. Some researchers study the use of multichannel electrode arrays or high-density EMG (large number of electrodes) strategy, while others explore the precise anatomical positioning approach (Hermens et al., 1997).

In pattern recognition based control, the most important steps are feature extraction and classification. Feature extraction involves transforming raw sEMG data into feature vector that is used to represent specific movement. Several features extractions methods were studied in this area which can be divided into three major domains: time domain features, frequency features, and time-frequency features. Some of time domain features include mean absolute value (Zecca et al., 2002), zero crossings (ZC), slope sign changes (SSC) (Englehart et al., 2003). These methods are effective but they are unable to detect the high frequency variations which occur in EMG signals due to dynamic movements, and that limits their ability for improvements of movements' recognition. Thus time-frequency domain methods came into picture.

Time-frequency domain features contains the combination of temporal and frequency information (Sejdi et al., 2009; Chowdhury et al., 2013; Nazmi et al., 2016). These features characterize the signal in time-frequency plane which allows an accurate description of the variability of frequency over time, providing plentiful non-stationary information of the EMG signals.

Short Time Fourier Transform (STFT) is a well-known time-frequency method which performs a mono-resolution analysis by applying a fixed size window on the signal. This can be considered as limitation in term of time-frequency resolution in

Karheily, S., Moukadem, A., Courbot, J. and Abdeslam, D.
Time-frequency Features for sEMG Signals Classification.
DOI: 10.5220/0008971902440249
In *Proceedings of the 13th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2020) - Volume 4: BIOSIGNALS*, pages 244-249
ISBN: 978-989-758-398-8; ISSN: 2184-4305

some cases of non-stationary signals. The Continuous Wavelet transform is another time-frequency method which perform a multi-resolution analysis by varying the scale of the mother wavelet according the analyzed frequency (Sun et al., 2015). The Discrete Wavelet Transform (DWT) performs a series of bank filter in order to explore the time-frequency content of the signal. CWT and DWT has been successfully applied on EMG signals (Sejdi et al., 2009; Canal et al., 2010). In this study, we apply the Stockwell Transform (ST) which can be considered as hybrid version between the STFT and the CWT (Stockwell et al., 1996).

Classification of hand motions based on the extracted features can be performed by a large variety of methods such as linear discriminant analysis (Negi et al., 2016), support vector machines (Leon et al., 2011), or artificial neural networks (Gonzalez-Ibarra et al., 2012).

In this paper, we aim to use sEMG to identify hand movements patterns based on time-frequency features. We will use recorded sEMG signals from Ninapro Project (Atzori et al., 2014), and apply two time-frequency transforms on several data sets that belong to different subjects. Then we will decrease dimension of extracted features by applying singular value decomposition (SVD) method. Our features' vector contains singular values and the most prominent time and frequency features, based on SVD (Hassanpour et al., 2004). Finally we will classify extracted features using two kinds of classifiers, and compare results achieved from each one.

2 MATERIALS AND METHODS

Data used in this study is recorded by surface electrodes placed on the arm of the subject, and each movement repeated several times, data is saved in matrix of dimension NxM, where N is the number of samples, and M is number of channels (electrodes)

In this section, we will give a brief description about used time-frequency methods, then we will present the used SVD methodology to decrease features' dimension.

2.1 Features Extraction

We applied two time-frequency transforms: the STFT and the ST. For each movement we apply this time-frequency transform on every channel (electrode) signal, then after decreasing feature dimension, we combine all values in one features' vector, and this vector will be used for classification.

2.1.1 STFT

Short-Time Fourier transform overcomes disadvantages of time domain by considering frequency variations over the time which is necessary for sEMG as it is stochastic and non-stationary signal. The STFT is applied in this paper in order to explore the frequency variation of the sEMG signal over the time. It applies a sliding window to the analyzed signal in which we consider the signal inside this window as stationary. Therefore, the Fourier transform can be applied in order to obtain the local spectrum:

$$\mathrm{STFT}(\tau,\mathrm{f}) = \int_{-\infty}^{+\infty} h(t)g(t-\tau)e^{-i2\pi \mathrm{ft}}\,dt \qquad (1)$$

Where h is the original signal, t is time, τ and f presents time of local spectrum and Fourier frequency, respectively, and g(t) is the used window function.

For comparison purposes, we chose a Gaussian window for STFT transform, in order to compare with ST. In addition the Gaussian window minimize the Heisenberg-Gabor relation which describes the compromise between the time and frequency resolution. Using the standard deviation σ, g(t) can be given as:

$$g(t) = \frac{1}{\sigma\sqrt{2\pi}}e^{\frac{-t^2}{2\sigma^2}} \qquad (2)$$

2.1.2 ST

The Stockwell transform is a hybrid version between the STFT and the Continuous Wavelet Transform (CWT). It uses a multi-resolution Gaussian window by varying its standard deviation over the analysed frequencies (Moukadem et al., 2015).

The ST can be derived from formula (1) by replacing σ in equation (2) by 1/f. Then the window function can be expressed as follow:

$$g(t) = \frac{f}{\sqrt{2\pi}}e^{\frac{-t^2f^2}{2}} \qquad (3)$$

Then the ST is defined as:

$$S(\tau,\mathrm{f}) = \int_{-\infty}^{+\infty} h(t)\frac{f}{\sqrt{2\pi}} e^{\frac{-(t-\tau)^2 f^2}{2}} e^{-i2\pi \mathrm{f}t} dt \qquad (4)$$

For each movement repetition, we get window of movement as matrix of size NxM where N is the number of samples, and M is number of electrodes. That gives M signals for each movement.

To summarize, for an electrode k, we have one signal [C_k], on which we apply time-frequency transform T(C_k), and this will be our initial features' matrix related to specific movement on specific channel.

2.1.3 SVD

The initial features' matrix we get from time-frequency domain is high dimension, and to be useful in movement identification, we still need to re- duce its dimension and extract the most valuable components in it (Wolczowski et al., 2017).

As we saw in initial features extraction, we get T(C_k) as initial time-frequency features on certain channel, and here we at first calculate SVD for this matrix:

$$U_k \Sigma_k V_k^* = SVD(T(C_k)) \qquad (5)$$

In order to keep the most important values of V_k and U_k, we compute their histogram over X bins denoted by $\tilde{V}_k$, $\tilde{U}_k$ and keep the two most important values.

Then for each channel, the feature vector is F_k will be defined as:

$$F_k = \{s_k^1, s_k^2, \tilde{v}_k^1, \tilde{v}_k^2, \tilde{u}_k^1, \tilde{u}_k^2\} \qquad (6)$$

Where $s^1{}_k$, $s^2{}_k$ are first two singular values, and $\tilde{v}^1{}_k$, $\tilde{v}^2{}_k$ are first two bins in $\tilde{V}_k$, also $\tilde{u}^1{}_k$, $\tilde{u}^2{}_k$ are first two bins in $\tilde{U}_k$. Finally the final feature vector of the observation will be:

$$F = \{F_1, F_2, \ldots F_N\} \qquad (7)$$

2.2 Classification

We use our built features' vector for identifying movements, this vector has 6xM values in different scales, so at first we normalize this vector so all values will be on scale [-1, +1]. In this study we use two kinds of classifiers to evaluate our extracted features; first one is K Nearest Neighbor (KNN) and second is Linear Discriminant Analysis (LDA).

2.3 Main Algorithm

The main algorithm is shown in figure 1, starting from raw sEMG data,

- Data normalization: we first normalize the data so we get standard deviation 1, and mean values 0. The normalized data matrix D will be used in features extraction.
- Time-frequency features extraction: we extract initial features on each channel. T_k=T(C_k) where T is the time-frequency transform we use, and C_k is signal coming from channel k.
- Build feature vector: we calculate final partial feature vector F_k=SVD(T_k) on each channel based on singular values and histogram of left and right SVs, and then we get the final constructed feature vector of the movement F=[F_1 F_2 … F_m], compound of features' vectors of movement on each channel.
- Classification: use collected observations, to feed chosen classifiers and evaluated extracted features. We apply this process on two different time-frequency domains (STFT, ST) and two classifiers (KNN, LDA).

3 RESULTS

3.1 Data Acquisition

In order to compare STFT with ST and KNN with LDA in the purpose of classifying hand gestures, we used database provided by Ninapro Project (Atzori et al., 2014). We chose exercise 1 from database 2 as it contains 17 different basic movements of fingers

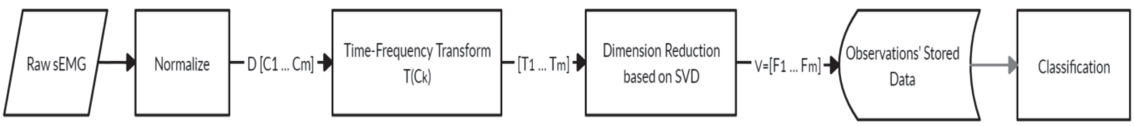

Figure 1: Main algorithm.

and wrist. The sEMG signals are provided together with their hand gestures.

Each movement in exercise is repeated 6 times, where each subject was asked to repeat movement and hold position for 5 second, followed by 3 second of rest. The muscular activity is recorded by 12 electrodes placed on subject's arm, so the recorded sEMG data were saved into matrix D of size Nx12 were N is recorded samples on channel. The sEMG signals are sampled at a rate of 2 kHz.

3.2 Features and Classification

Using the data described above, we will apply both STFT and ST on the raw data, and then we will build feature vector based on singular values and histogram of left and right SVs.

In order to test the accuracy of our proposed method, we applied it on 10 subjects. The raw sEMG contains recorded samples on each channel for each movement.

Figure 2: physical movement. On the left is movement 3. On the right is Movement 4 (Atzori et al., 2014).

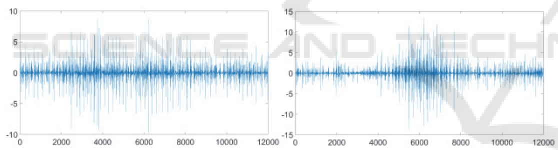

Figure 3: raw sEMG signal. On the left is movement 3 on channel 1. On the right is movement 4 on channel 1.

For each channel signal, we calculate time-frequency transform. We use sampling frequency 2 kHz, and with frequency rate between 1 and 200 Hz, as most sufficient sEMG frequencies varies in this range. For the STFT we choose value σ = 0. 005 (equation (2)).

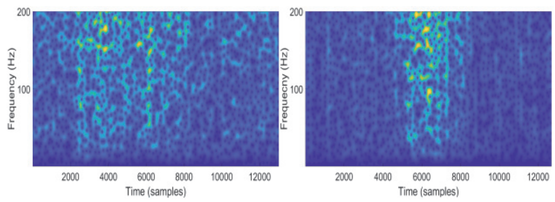

Figure 4: STFT. On the left is movement 3 on channel 1. On the right is movement 4 on channel 1.

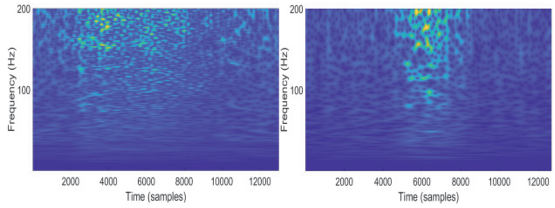

Figure 5: ST. On the left is ST for movement 3 on channel 1. On the right is ST for movement 4 on channel 1.

The chosen value σ = 0. 005 promoted time resolution, while in the case of ST, it gives lower time- resolution for low frequencies (as you can see in figure 4 and 5) since the standard deviation of the Gaussian window in the time-domain varies as 1/f.

We construct final features' vector from SVD singular values and histogram of left and right values, then we combine results from all channels into one vector.

As a result from previous steps, we get features' vector of dimension 72 for each observation (as we have 12 channels, and for each we get 6 feature values). We use these observations' features to train both KNN and LDA classifiers.

Results are given in table 1. We use k-fold cross-validation (with k=5) and record the mean accuracy of classifications.

By using STFT as time-frequency transform we get mean accuracy rate 92.60% with KNN classifier, and we get 88.57% accuracy with LDA classifier.

For S-Transform, we get mean accuracy 81.80% by using KNN classifier and 84.93% by using LDA.

Table 1: Classification results, with best result for each subject in bold.

Subject	STFT		ST	
Classification	**KNN**	**LDA**	**KNN**	**LDA**
Right Handed Male	**93.14**	87.25	77.45	75.49
Left Handed Female	**90.19**	88.24	78.63	83.53
Right Handed Male	**96.08**	91.18	87.25	90.20
Right Handed Male	91.18	**92.16**	85.29	85.29
Right Handed Male	**92.16**	88.24	78.43	87.25
Right Handed Male	**90.39**	82.35	76.47	88.23
Right Handed Male	**96.08**	94.12	78.43	82.35
Right Handed Male	**94.20**	88.24	88.47	86.39
Right Handed Male	**92.44**	85.25	80.67	84.40
Right Handed Female	**90.20**	88.64	86.82	86.59
Average	92.60	88.57	81.80	84.93

For KNN classifier, we tried different values of K, where K in {1,3,5}, and we got best mean accuracy when K=1 with classification accuracy 92.60% then when K=3 with accuracy 88.16% when applied with STFT method.

By looking on confusion matrix for classification of subject 3 dataset, we notice that classification fails to distinguish between two movements (4 and 5) and that increases error rate, as shown in figure 6.

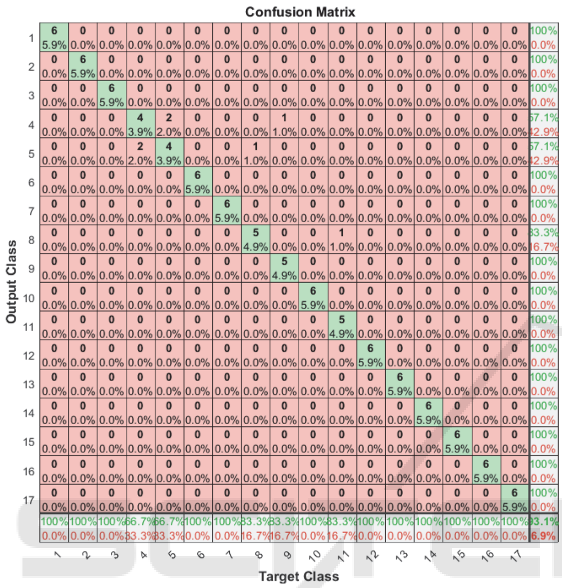

Figure 6: Confusion matrix, subject 3.

In movement number 4 subject opens four fingers and in movement number 5 he opens five fingers, so these two movements are near to each other's, and in fact it could be hard to classify unless we focus on getting more distinguished signals while doing data acquisitions.

As result, with STFT time-frequency transform, we get better classification, and with adding histogram of SVD, classification results were significantly improved compared to similar study on this database (Anti et al., 2014) with classification rate 82.77% for 12 different movements.

4 CONCLUSION

In this study, we used two different time-frequency transforms to extract features of different movements of hand. The extracted features are evaluated by using two classifiers.

For features extraction, we used novel method in dimension reduction and put both left and right SVs into consideration, by using first two bins in their histograms.

Results show that using STFT with KNN has better results with improved classification accuracy 92.60%. We improved classification accuracy obtained on same database, and we showed comparison between using two time-frequency transforms for features extraction.

Future work will focus on adding more subjects to evaluate the proposed method. Another optimized time-frequency representation can be also applied and compared with current results.

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