An Inventive Quadratic Time-Frequency Scheme Based on Wigner-Ville Distribution for Classification of sEMG Signals

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Abstract—**Electromyogram signal is a biopotential signal that may be measured on the surface of contracting muscles representing neuromuscular activities. This signal may be utilized in various applications such as clinical diagnosis of diseased neuromuscular systems and as a measurement tool for evaluation of rehabilitation activities. Another recent application is the usage of EMG signal in design and implementation of neural controlled prosthesis hands. For this purpose appropriate features of EMG signal are required such that intended hand movements may be recognized correctly. In this work we considered a new method based on quadratic time-frequency representation namely Wigner-Ville distribution (WVD) to extract required information. In the proposed approach, initially WVD coefficients for each class were calculated. Next average coefficients for all the signals in each class were obtained. Then cross-WVD was found by using acquired average WVD coefficients with signals in each class and finally the number of zero crossing (ZC) of cross-WVD coefficients were utilized as suitable features. Our proposed approach provided satisfactory results with a recognition average accuracy rate of 91.3% for six classes of movements. On the other hand, for unprocessed (raw) WVD coefficients the average accuracy of the six hand movements was registered at %33.7.**

Keywords— **Electromyogram signal, quadratic time-frequency, Wigner-Ville distribution**

I. INTRODUCTION

The EMG signal measures electrical currents generated in muscles during their contractions. The noninvasive EMG signal, recorded at surface of the skin (sEMG) is the current state of the art technique for the control of prosthetic devices. The abilities of the currently existing hand prosthesis are typically limited to opening and closing. This matter limits the usefulness of such devices considerably compared to many degrees of freedom in a normal hand. To design the more resembling devices one needs to extract useful information from EMG signal in order to generate enough discrimination among hand movements.

Hudgins et al proposed that there is a significant temporal structure in transient sEMG bursts and these structures generate required information for pattern recognition [1], [2]. However, their results demonstrated that although classifiers may have obvious improvements in the system classification rate but ultimately, it is the actual sEMG signal representation that has the most effect.

As EMG signal patterns have characteristics in both time and frequency domains, time-frequency representation (TFR) was found to be a viable candidate for EMG features extraction [2] - [7]. TFR can localize the energy of signal in time and in frequency and thereby provides a more accurate description of the EMG signal [2], [8], [9], [10]. Englehart et al used three types of linear TFRs, namely short time Fourier transform (STFT), wavelet transform (WT), and wavelet packet transform (WPT) [2], [3]. He showed that time-frequency features increase the accuracy of EMG pattern recognition system and demonstrated that by representing the signal in a suitable manner the linear classifier exceeds the performance of other classifiers.
Quadratic Time-frequency, another type of TFR, was developed to overcome certain shortcomings of linear TFR. Wigner-Ville distribution, a special case of Cohen's class of distribution, is based on the use of autocorrelation function for calculation of the power spectrum [11] - [16]. In this work we propose a new method based on Wigner distribution (WVD) to generate appropriate EMG features set.

II. METHODOLOGY

A. Formal Scheme of sEMG Pattern Recognition System for the Control of Prosthesis Hands

The overall scheme of sEMG pattern recognition system that we used in this work is depicted in Figure 1. We considered four major parts including, sEMG pre-processing and conditioning, feature extraction, dimensionality reduction and classifier.

In this work we used two channels of differential surface electrodes for collecting sEMG signal [1]. The goal of pre-processing step was to prepare and amplify the signal for the subsequent parts resulting in a reduction of artifact noise [17]. During the feature extraction step, sEMG signal is processed in order to emphasize relevant structures. In this phase we introduced our proposed approach based on the quadratic time-frequency representation, by use of Wigner distribution. Next, we utilized a dimensionality reduction technique to simplify the task of the classifier. For this part of the system, the principle component analysis (PCA) was utilized. After calculating EMG feature set we used Fuzzy inference system (FIS) as an intelligent classifier to discriminate between hand movements [18], [19], [20]. To design sEMG pattern recognition system in this work, we used a roster of four healthy subjects. Six hand movements were considered and sEMG signal for each was recorded. These movements were Hand opening (Ho) and closing (Hc), pinch (Pi), thumb flexion (Tf), wrist radial flexion (Wf) and extension (We).These movements are shown in Figure 2. For each class of movements 100 signals were collected. We divided our acquired signals into two categories. First category was utilized as a training data set and the second was employed as a test data set. Each of these sets included 50 signals.

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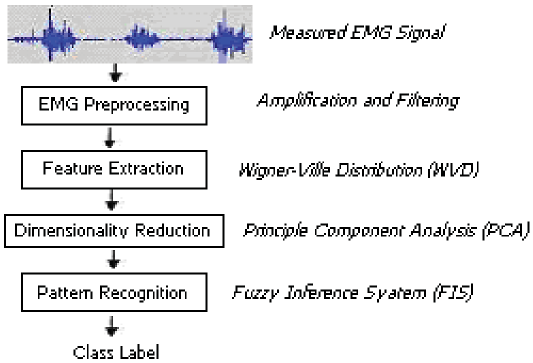

Fig.1. Conventional Scheme for hand prosthesis control

B. Wigner- Ville Distribution

The Wigner distribution (WD), a major quadratic time-frequency representation was originally introduced in a quantum mechanical context by Wigner in 1932 [11]. In 1948 Ville introduced the WD in a signal analysis context [12]. The WVD (windowed or smoothed versions of WD) can be used in different application such as biological and medical signal analysis [11] – [16].

Time frequency representations such as WVD (or Wigner-Ville spectrum) are suitable for non-stationary or time varying signals. The WVD is functionally similar to a spectrogram. On the whole it gives better temporal and frequency resolution, at the expense of introduction of certain artifacts and negative values corresponding to negative energy, which is physically not possible and results in significant defect.

These are known drawbacks with the WVD Spectrum although there are ways to compensate. In other words, even considering the artifacts, the WV spectrums utilized in our study have very useful information, more so than the spectrograms that we employed for comparison.

In our study we used the WVD in the application of EMG pattern classification to identify hand motion commands. Quadratic time-frequency representations are based upon estimating an instantaneous power spectrum using bilinear operation on the signal itself. Although real-time quadratic methods are computationally intense, their high resolutions provide valuable insight for our desired pattern recognition application. For a continuous time signal x (t), the WVD is defined as [16].

$$W_x(t,f) = \int_\tau x\left(t+\frac{\tau}{2}\right)x^*\left(t-\frac{\tau}{2}\right)e^{-j2\pi f\tau}d\tau \qquad (1)$$

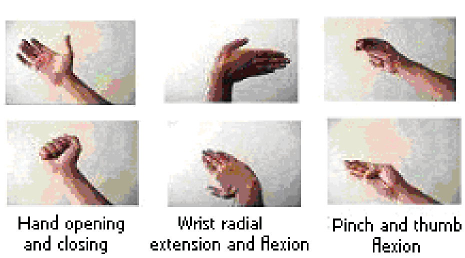

Fig.2. The six classes of motion used in the two channel experiment.

The WVD is a quadratic time-frequency signal representation that can be loosely interpreted as an energy distribution over the TF plane. The definition for the WVD of a discrete time signal x[n] is given as follows [16]:

$$W_x(n,\theta) = 2\sum_{m=-\infty}^{\infty} x[n+m]x^*[n-m]e^{-j4\pi m\theta} \qquad (2)$$

where θ denotes normalized frequency. In general the 'Wigner Distribution' of a signal x(t) is defined as above, while the 'Wigner-Ville Distribution' is defined as the Wigner Distribution where $x(t)$ is the analytic associate (also known as "analytic signal" or "complex signal") of $s(t)$. The analytic associate $x(t)$ of a signal $s(t)$ is defined as: $x(t) = s(t) + i\,\mathrm{H}[s(t)]$ where $\mathrm{H}[s(t)]$ is the Hilbert Transform of the signal $s(t)$ [21].

A major issue in the application of the quadratic TFR is the existence of cross-term in its distribution. This is due to interference between the positive and negative frequency components in the double sided spectrum of the real valued signal. It follows that the analytic equivalent of the real signal may be used in a WVD analysis. Regarding equations (2) and (3), it is evident the WVD takes the Fourier transform of the instantaneous autocorrelation function, but only along time (t) dimension. The result is a function of both frequency and time. Figures 3a through c, depict the characteristic of WVD, WT, and STFT, respectively. As illustrated in Figure 3, the WVD gives better frequency and temporal resolution. Therefore the WV spectrum contains useful information, more so than the spectrograms and scalogram. The main reason for this advantage is that the time-frequency resolution for quadratic TFR is not limited by the Heisenberg bound. The limitation of linear TFR is due to the effect of a local time window. If this window is more resolved in time the frequency resolution suffers because the effective width of its Fourier transform increase and vice versa. It is important to note that we did not utilize the WVD coefficients directly resulting from equations (2) or (3). Instead we developed a new method for extracting EMG features from WVD coefficients, outlined in the next section.

C. Solving the WVD Drawback to Create a Powerful EMG Feature Set

The WVD may be interpreted as a two dimensional distribution of signal energy over the time frequency plane [16]. The WVD satisfies a large number of desirable mathematical properties. In particular, WVD is always real-valued it preserves time and frequency shifts and satisfies the marginal properties. The absence of a windowing function yields a very high dimensional TFR that offers superior resolution to any linear method balanced by high computational cost.

To overcome this drawback we used pseudo Wigner-Ville (PWD) by using two smoothing windows: a spatial averaging window $g(l)$ and a spatial frequency averaging window $h(k)$ [22].

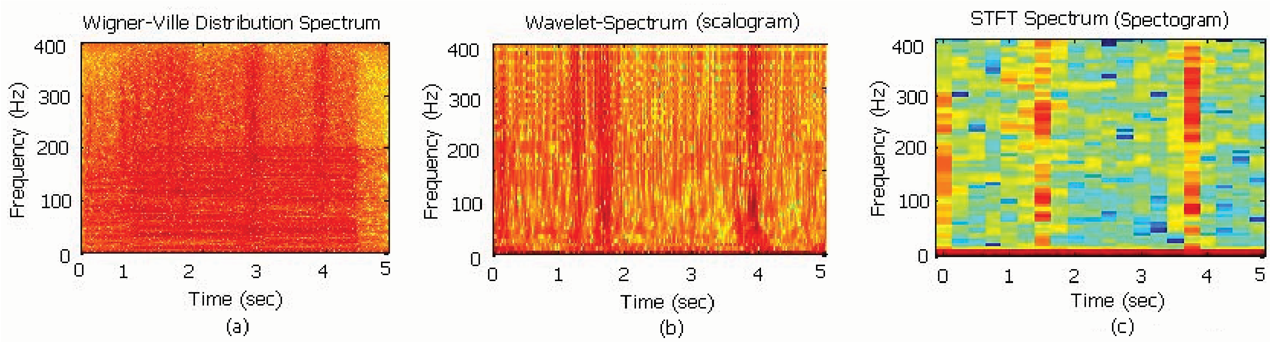

Fig.3. Comparing the time- frequency distribution of Typical EMG signal for three TFR methods (a) WVD, (b) WT and (c) STFT

Frequency smoothing is equivalent to spatial windowing and vice versa. The resulting smoothed Wigner-Ville distribution is:

$$SWD(n,f) = \sum_{m=-\infty}^{\infty}\sum_{k=-\infty}^{\infty} g_M(m)h_N^2(k)x(n+k+m)x^*(n-k+m)e^{-j4\pi fk} \quad (3)$$

This double smoothing operation produces an improvement in the cross-terms reduction. By using analytic signal shown in equation (3), interference term as well as computational complexity is eliminated due to the absence of negative frequency components. To create the WVD effective features set we needed to emphasis on the main advantage and compensate for its disadvantage. To better characterize the above motioned notions the factors of our feature set design are introduced in Table I where proposed WVD is briefly outlined.

TABLE I
ADVANTAGES AND DISADVANTAGES OF THE PROPOSED WVD EMG FEATURE SET

Advantages	- complete time-frequency view - high time-frequency resolution - the time and frequency concentration is preserved exactly - invariant to shifts in time and frequency - it is possible to recover the original signal, except for a constant, from the distribution
Disadvantages and their solutions	-computational complexity → utilization of smoothing WVD (PWD) and PCA as dimensionality reduction techniques - cross terms→ using analytic signal and PWD - dispersion of information → using filtered EMG signal for frequency interval (20-500Hz)

III. RESULTS

A. Constructing a New sEMG Feature Set Based on WVD

To construct EMG feature set for the task of recognition of hand movements, initially WVD was calculated for all signals in each class. Then the acquired coefficients were averaged to get the WVD sample for each class. By implementing this step we eliminated the similarity between signals in different classes and we were able to reduce the effects of noise and artifacts on EMG signals. Next the cross-WVD was computed by using WVD sample and the EMG signals in each class. Finally we used zero crossing for the acquired cross-WVD as the desired feature.

To simplify the task of pattern recognition for classifier we used PCA for dimensionality reduction. Table II illustrates our approach to create EMG feature set.

TABLE II
THE PROCEDURE FOR CONSTRUCTING EMG FEATURE SET BASED ON WVD

Steps	Comments
1	Computing the auto WVD for all signals in each class
2	Computing the WVD sample by averaging the auto WVD for each class
3	Computing the cross-WVD by using the WVD sample with all the signal in each class
4	Using the number of zero crossing (ZC) as a suitable feature for the acquired cross-WVD coefficients + PCA

B. Experimental Results

In this study six classes of hand movements were utilized and upon implementation of the pattern recognition system, the accuracy of the system was evaluated. To adequately compare and test the ability of our proposed quadratic TFR based method for EMG feature extraction, we also examined STFT, WT, and unprocessed (raw) WVD. Table III illustrates the acquired results for these features. To construct EMG feature set for STFT and WT, we considered the most effective parameters. For example in the case of STFT, we utilized Kaiser Window with 125 ms length [23]. Similarly for WT, we applied symlet7 wavelet with a maximum of nine levels of decomposition.

The acquired results of proposed method based on quadratic TFR discriminated soundly among the six hand movements with average accuracy of 91%. On the other hand, when EMG features from unprocessed WVD were utilized, a maximum recognition rate of %46 was registered for the hand closing movement and the average accuracy dropped to 33%. By inspecting the results noted in Table III, it becomes evident that our proposed method was superior to linear TFR for the recognition of hand movements.

TABLE III
COMPARING THE ACQUIRED RESULTS BY USING THE LINEAR TFRs AND PROPOSED QUADRATIC METHOD TO IDENTIFY HAND MOTION COMMANDS

Different type of TFRs to construct EMG feature set		Classification Rate for Different type of Hand movements (%)						
		Ho	Hc	We	Wf	Pi	Tf	Aver
Linear TFRs	STFT	74	86	76	78	82	72	78
	WT	82	92	86	80	84	78	83.7
Quadratic TFRs	Unprocessed WVD	38	46	28	32	34	24	33.7
	Proposed WVD	94	100	92	86	92	84	91.3

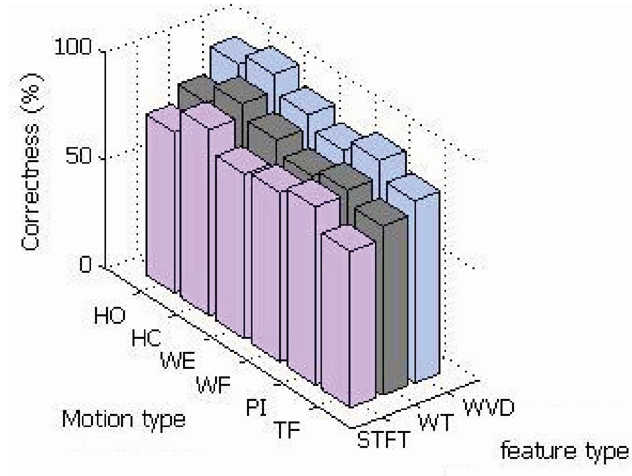

Fig.4. Comparing the acquired results by three types of TFRs in the application of identify hand movements

V. CONCLUSION

In this study a new quadratic time frequency method based on WVD for sEMG signals was introduced. Our approach was to apply the average auto-WVD as a WVD sample to compute cross-WVD and use the number of ZC as a suitable EMG feature. By implementing this novel approach, a significant improvement in hand motion identification was reached.

Our proposed method was successfully evaluated through a pattern recognition scheme. Furthermore, as noted in Figure 4, the created new WVD based method provided the best recognition accuracy for each individual hand motion command as well.

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