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Research Article

Knee Abnormality Prediction based on Power Spectrum Analysis of Surface EMG Signals

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Abstract

This article proposes an improved extraction feature for lower limb knee abnormality prediction application using surface EMG raw data. Public UCI dataset is chosen for system evaluation, where each subject was informed to perform three different motions of walking, standing up, and sitting down. In feature extraction, EMG spectrograms are derived using Short Time Fourier Transform (STFT), power spectrum of range 10-250 Hz is chosen, then, the linear coefficients of EMG power spectrum for each frequency bin during time are extracted as a final feature of size 30x2. For system prediction, Convolutional Neural Network (CNN) with other two common machine learning classifiers were constructed. The proposed system experiments proves that EMG signals of Semitendinosus(ST) muscle with CNN classifier produces the highest accuracy of 95%.

Keywords: Knee Abnormality; EMG Signal; CNN Classifier; Prediction System; UCI Database

Introduction

Electromyography (EMG) is a medical test for recording the electrical activity of skeletal muscles [1-3]. The recorded EMG signals can be later analyzed to locate abnormalities, and muscle activity level. In artificial intelligence revolution, EMG is one of the main sources or inputs to Human Computer Interface (HCI) technology where it is possible to be powerful tools in many daily life applications such as robotics, limbs motor control, motion disorders and therapy, limbs and knee abnormality prediction [4-7].

Actually, the principle of knee normality prediction based on surface EMG signals has attracted many researchers. For example, Vijiayvargiya et al. [8] used the same UCI dataset, as in our study, in two important articles; in the first one, they extracted up to eleven time-domain features and achieved a high accuracy of 91% with Extra Tree classifier; in the second one [9], they implemented wavelet technique in signal pre-process stage, and obtained a higher accuracy of 93.2%.

In Kohlschuetter et al. [10] Proposed a new probabilistic model for prediction system, and depended on PCA and NMF selection methods for feature dimension reduction purpose. Finally, they got an accuracy result of 86%. In Herrera-Gonzalez et al. [11] Study, they depended on Wavelet Transform (WT) to extract the time-frequency domain in feature extraction step. For classification, traditional Neural Network (NN) was constructed and obtained an accuracy of 80%.

Furthermore, recent research for Issa et al. [12] used the same UCI dataset. They extracted the local range texture features using Short Time Fourier Transform (STFT) spectrogram, and got an accuracy of 91% with deep Convolutional Neural Network (CNN).

Depending on the previous literature studies, it is obvious that this research still needs more improvement and enhancement. Most works depended on calculating features with huge dimensions, used complicated feature selection methods, and/or added constraints to increase the accuracy results [8-12].

In this article, an improved lower limb knee abnormality recognition system is provided based on the linear changes of EMG power spectrum of each frequency bin during time. Public UCI database is chosen in this study, Short Time Fourier Transform (STFT) spectrogram is used to get the time-frequency domain of EMG raw data. Then, a combination of mathematical calculations is implemented to extract the coefficients of EMG linear power spectrum during time. For system prediction, Convolutional Neural Networks (CNN) and other two traditional machine learning classifiers are constructed for evaluation purpose. The main achieved contributions in this paper are as follows:

1. An improved feature is provided using EMG linear spectrogram variability during time, which produces reliable results in knee abnormality recognition.
2. This study proves the validity of Semitendinosus (ST) muscle with deep Convolutional Neural Network (CNN) in knee abnormality system prediction.

This paper is organized as follows; 'Materials and Methods' section presents the proposed methodology including feature extraction and prediction in detail. 'Results and Discussion' section provides the experimental outcomes with results, analysis and comparisons, where the final section lights up the net conclusion, and gives some recommendations for future work extension.

Materials and Methods

The prediction system flowchart is illustrated in Figure 1. It comprises of dataset acquired and pre-processing, feature extraction, and classification stages.

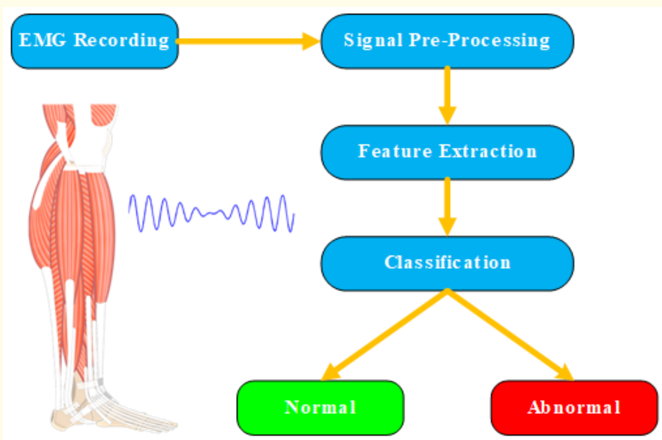

Figure 1: The Proposed System Flowchart.

Data Acquisition and Pre-Processing

The public UCI dataset of surface EMG [13] is chosen in this study for feature extraction evaluation. It has a total of 22 participants' recordings where 50% of them are healthy and do not have any preceding case for knee problems. All participants were requested to perform three movements of walking, standing, and sitting. EMG raw data was detected using four EMG channels pasted on Recto Femoral (RF), Femoral Biceps (FB), Vastus Medial is (VM), and Semitendinosus (ST) muscles. The recorded EMG data was transferred to Data log software via real time Bluetooth technology, and sampled to 1 kHz. In pre-processing, a band pass filter was implemented for frequency range selection of 10-250 Hz.

Feature Extraction and Classification

The proposed extracted feature performs the linear change of EMG power spectrum density for each frequency bin during time. Hence, a prior step for time-frequency domain transformer is needed. Actually, there are several time-frequency domain transformers, and each type is superior in some applications. In this work, the common Short Time Fourier Transform (STFT) technique is implemented. Feature extracting stage can be illustrated in the following sequential steps:

1. Calculate the Short Time Fourier Transform (STFT)

In general, STFT is extracted by sliding an appropriate window function over the time domain signal, and then finds the discrete Fourier transform for each windowed data [14, 15]. Although frequency domain analysis achieves good results in many applications [16], time-frequency domain gives a deeper understanding especially in nonstationary signals such as EMG signals. STFT conversion is getting using Eq.1 [14, 15]:

$$STFT_m(f) = \sum_{n=-\infty}^{\infty} x(n)w(n-mH)e^{-j2\pi fn} \text{......}(1)$$

Where x(n) is the original EMG surface signal; m is the frametime; H is the frame overlapping distance; w(n) is the window function. Hann window function is chosen for conversion, which is defined as [16]:

$$w(n) = 0.5\left(1-\cos\left(2\pi\frac{n}{N}\right)\right), 0 \le n \le N \text{.....}(2)$$

Where N is the total number of samples.

STFT provides the spectrogram of EMG power spectral density in both time and frequency domains. Figure 2 provides an example of STFT conversion of EMG data for normal participant case during walking motion.

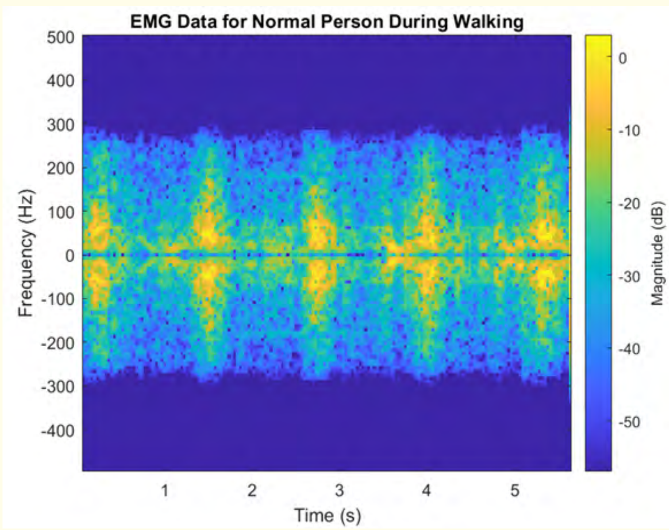

Figure 2: EMG Data for Normal Participant During Walking Motion.

2. Select the time-frequency data within the range of 10-250 Hz.

Several previous related works approved the effectiveness within this frequency range [12, 18].

3. Extract the coefficients of power spectrum linear relation for each frequency bin during time

The linear power spectrum at each frequency bin is approximated according to the following relation:

$$For\ \forall\ f\ bin,\ P(x) = ax + b \quad ....(3)$$

Where P(x) is the power spectrum during time; a and b are the extracted coefficients.

For knee abnormality prediction, Convolutional Neural Network (CNN), and other two traditional machine learning classifiers were constructed and tested.

Figure 3 presents the basic structure of deep Convolutional Neural Network (CNN). It includes the five basic layers of input layer which could be multi-dimensional data, Convolution and Pool layers for calculating the neurons deep features, and reducing the spatial dimension, respectively; fully connected layer for calculating the class label, and finally, the output layer [19, 20].

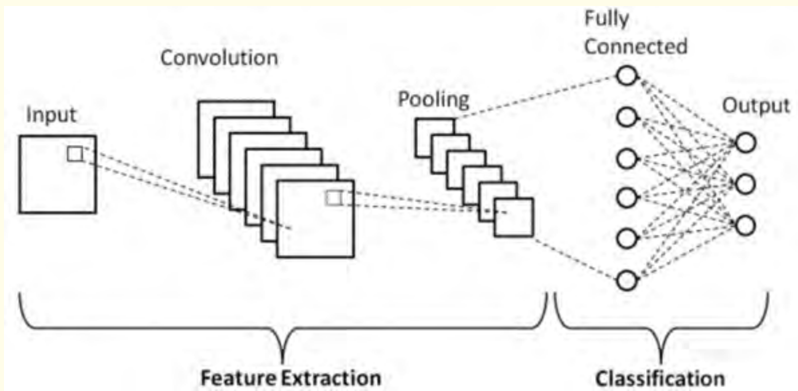

Figure 3: CNN Classifier Structure [18].

Results and Discussion

In experiments, MATLAB 2021 was used, and codes were tested using a laptop equipped with an Intel(R) core(TM) i7-11800 2.3 GHz CPU.

First, EMG signals for all participants were pre-processed, STFT spectrogram was calculated for all EMG channels using Hann window function of length 128, and overlapping of 75%. Finally, the two linear coefficients of power spectrum at each frequency bin (10-250 Hz) were calculated to form the final feature of size 30x2.

Convolutional Neural Networks (CNN), Support Vector Machine (SVM), and Linear Discriminant Analysis (LDA) were constructed for evaluation purpose.

- CNN classifier has input Layer of size 30x2; convolutional layer of two filters, each one of size 2x2, and a stride of one-step; pooling layer of one filter of size 2x2 and a stride of one step; fully connected layer with lose function of SoftMax; output layer of two labels (Normal, and Abnormal). The total Epochs number and learning rate are 250, and 0.0001, respectively.
- SVM classifier with Polynomial kernel function.
- LDA classifier with Pseudo linear discriminant.

Table 1 below lists the average accuracy results for each EMG channel. On the other hand, Figure 4 presents the average accuracy results of the constructed classifiers.

Classifier	RF Muscle	BF Muscle	VM Muscle	ST Muscle
CNN	80%	81%	85%	95%
SVM	65%	70%	65%	71%
LDA	55%	66%	55%	70%

Table 1: Average Accuracy Results for each EMG Channel.

Depending on the experimental outcomes, the extracted feature generally produces better results in Knee abnormality prediction for Semitendinosus (ST) muscle. Moreover, it is clear that the best outcomes were obtained for CNN classifier. Up to our knowledge, deep learning classifiers including the powerful CNN exceed the traditional machine learning techniques; it has the ability to learn the deep features for large dimensional data inputs [12, 18].

Compared with recent related studies, the proposed work overcomes the previous problems and constraints, such as generating features of high dimensions, using complex feature selection methods, and/or hybrid feature [8-11].

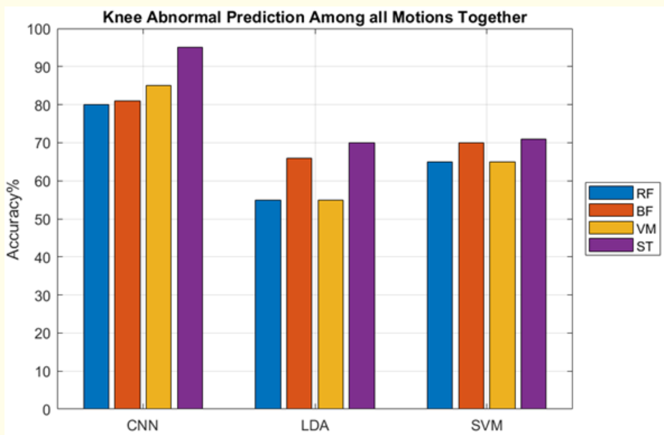

Figure 4: Average Accuracy of the Tested Classifiers for each Muscle.

Conclusion

The proposed article provides a new lower limb knee abnormality checking using EMG signals of ST muscle. The linear variability of STFT spectrogram for each frequency bin of range 10-150 Hz during time is used for feature extraction process. Experimental results show that deep Convolutional Neural Network (CNN) obtained the highest accuracy results among other traditional machine learning classifiers. In future work, other types of spectrogram transformers and deep learning methods will be tried to improve the prediction system.

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