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Design and Implementation of DWT based EMG Signal Processing for Upper Limb Prosthesis

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ABSTRACT: Electromyography (EMG) signals are the electrical manifestations of muscle contractions. EMG signals may be weak or at a low level when there is only a small movement in the major corresponding muscle group or when there is a strong movement in the minor corresponding muscle group. Moreover, in a single- channel EMG classification identifying the signals may be difficult. However, weak and single-channel EMG control systems offer a very convenient way of controlling human–computer interfaces (HCIs). Identifying upper-limb movements using a single-channel surface EMG also has a number of rehabilitation and HCI applications. The fractal analysis method, known as detrended fluctuation analysis (DFA), has been suggested for the identification of low- level muscle activations. This study found that DFA performs better in the classification of EMG signals from bifunctional movements of low-level and equal power as compared to other successful and commonly used features based on magnitude and other fractal techniques.

KEYWORDS: Convolutional neural network (CNN), deep learning, myoelectric signal, simultaneous control.

INTRODUCTION:

The central neural system regulates muscular contraction by adjusting the recruitment number and firing rate of motor units (MUs). Actuation of signals from the MUs is initiated by motor neurons in the spinal cord, and the combined action of MUs results in composite action potentials that can be recorded as myoelectric Signals.The CNN model distinguished the necessary information on its own irrespective STEMS, Kernel of the first convolution layer of one model. (a) Model of baseline (WL = 512 ms). (b) Model of baseline (WL = 1024 ms). (c) Model of cross-subject adaptability (WL = 512 ms). (d) Model of cross-subject adaptability (WL = 1024 ms). We evaluated the model in terms of three distinct aspects of adaptability, namely to electrodes shifting, cross arm, and cross subject. The prediction accuracy of the conventional method, SVR, declines as the practice difficulty increases. Through the acquisition of additional knowledge from multiple subjects, however, with our CNN method, cross-subject accuracy can even exceed between-arm accuracy. Owing to the nature of the FMM device that we used, it was possible to establish a standard coordinate system among various subjects, and the actual wrist forces were measured exactly according to this standard. . In the absence of a device for measuring the joint force and establishing a standard across subjects, it is difficult to predict the outcomes from one subject to the next. The results with regard to the cross-subject confusion matrix and the kernel shape of the convolution layer all indicate that YANG et al.: DECODING SIMULTANEOUS MULTI-DOF WRIST MOVEMENTS FROM RAW EMG SIGNALS USING A CNN 419 the model acquired more knowledge from multi-subject than single- subject training. In light of this finding, a model with the capacity for generalization could be established for new subjects.

LITERATURE REVIEW:

We have introduced a deep learning method, CNN, for the decoding of multi-DOF wrist movements directly from raw EMG signals. With it, we were able to select a large WL directly and to handle excess information. As electrical manifestations of neuromuscular activities, EMG signals collected noninvasively by surface electrodes can provide a good estimate of the extent of muscle contraction and EMG signals with variable variances S - EMG Signal Compression in One Dimensional and Two Dimensional Approaches [2], has been widely adopted in neuropathological examinations for selecting EMG-Contaminated EEG Channels in Self- Paced Brain-Computer Interface Task Onset [3], an Enhanced Human-Machine Interface for Upper-Limb Prosthesis Control With Combined EMG and NIRS Signals [4]. Commercial products such as the Myo Armband (Thalmic Labs, USA) and multi-functional EMG controller (Coapt, LLC, Chicago, USA) and also improving the Performance Against Force Variation of EMG Controlled Multifunctional Upper- Limb Prosthesis for Transradial Amputees [7]. Compared with raw EMG signals, hand-engineering features in low-dimensional space can reduce PR complexity significantly, but there is an inevitable loss of important underlying information from the myoelectric signals. Various features, or classifiers, have been shown to possess EMG-Based Continous Control Scheme With Simple Classifier for Electric- Powered Wheelchair [10] . There are a large variety of bio-sensing technologies designed for improving control functionality, such as ultrasound imaging electroneurography, and near infrared spectroscopy.

In this paper, we describe the first effort to use CNN to decode 3-DOF wrist movements directly from the raw EMG signals. The selection of window sizes and the influence of this selection on the model are also discussed in determining the configuration of the model. We further tested the capacity for generalization of the network across subjects, that is, the tolerance of the method for individual differences when training on and predicting various users. The model based on multi-subject training could directly accomplish the rough control for a new subject without further training. This would reduce the training time for a new patient adapting the prosthesis device. Lastly, based on our new method, we identified certain connections between raw EMG signals and the force involved in multi-DOF movements that may serve as a general predictive model for most users in situations involving simultaneous EMG control.

EXISTING SYSTEM:

In existing system, the major problems are actual prosthesis are mostly limited to intrinsic visual and acoustic feedback, available by observation of the prosthesis and sounds of the motors ,as it is the case for vibrotactors or pressure. The biggest problems is that most models have been tested extensively in controlled environments but the prove for robustness under the non-stationary conditions of daily life is often missing. This needs to be reflected in the evaluation procedures. Furthermore, to achieve real-time usability, appropriate design of the prosthetic device, feature extraction and classification techniques should be properly investigated and implemented. The process should not be in manual analysis, Continuous wavelet analysis and the distance of the wavelets is based on signal classification

DISADVANTAGES OF EXISTING SYSTEM:

- Not applicable for multiple signals for abnormal detection in a short time.
- Loss of details due to shift invariant property.
- Difficult to get accurate results.

PROPOSED SYSTEM:

In proposed system, the problems in existence are overcome by, some techniques . It becomes a pre processing system and the system has advanced to use Discrete wavelet analysis instead of Continuous wavelet analysis after investigation. Gray scale Co- occurrence matrix is introduced so , the accuracy of the signals or wavelet can be efficient. The sound of the machines is reduced because of using EMG ports. They can be used to give a accurate wavelet signal in a discrete form.

ADVANTAGES OF PROPOSED SYSTEM:

- The algorithm Proves to be simple and effective
- Gray scale Co-occurrence matrix extracts the features accurately

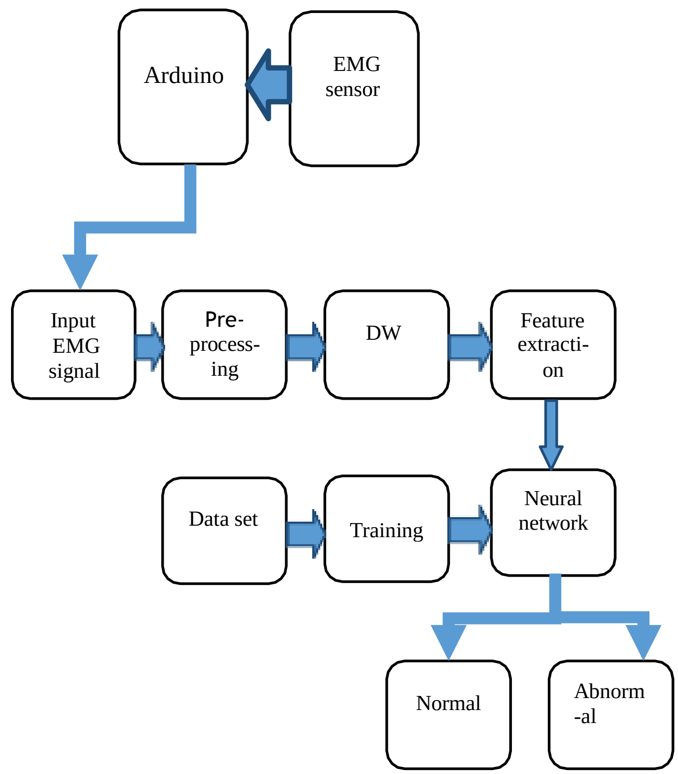

Fig.1: DWT based EMG signal processing

RELATED SEARCH

A. SUBJECT

Eleven able-bodied subjects (all of whom were male and righthanded) participated in the experiments. Their average age was 25.7 ± 1.4 years and their average height, weight, and body mass index (weight/height2) were 175.7 ± 5.6 cm,

70.0 ± 8.5 kg, and 22.3 ± 1.4 kg/m2, respectively. None of the subjects had any history of neuromuscular disease. We provided them with a short description of the purpose and nature of the experiments, and all of them signed an informed consent form. The experiments were also approved by the university's ethics committee and were designed to conform to the declaration of Helsinki.

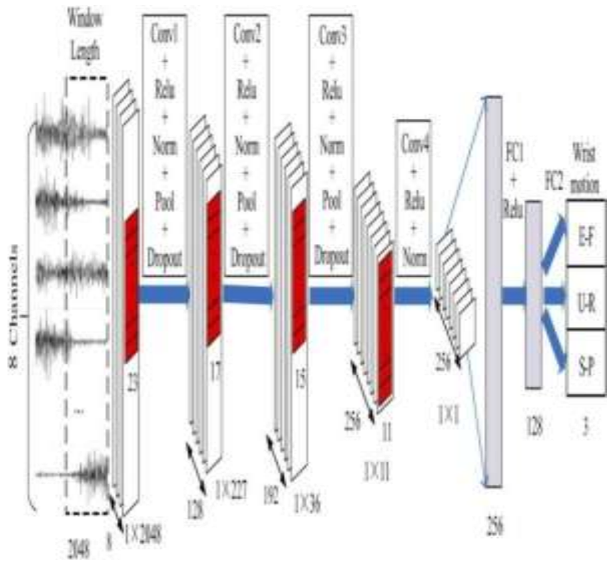

Fig. 2. Structure of the CNN model used to decode 3-DOF forces (WL = 1024 ms). The input participates in the calculation as arrays and its information can be decoded gradually along these cascaded layers.

B. EXPERIMENT PLATFORM

The first step in establishing a predictive model for decoding multi-DOF activities (involving either motion or force) is to collect a sufficient number of training samples. Thus, supervised wrist activities are detected simultaneously along with the raw EMG signals. In previous work, we developed a platform for collecting these signals contains a wrist force-to-movement mapping device (FMM) of our own design. The springs on the FMM make it possible to map the force and position of the wrist joint. The subjects must exert sufficient force to perform various wrist movements in a semi-constraint manner. In this way, the movements mimic closely the natural situation during reach-and-grasp activities, and the elicited multi-DOF wrist force can be quantified accurately through the relevant ones. A laser on the device makes it possible to interpret the extension-flexion (E-F), ulnar-radial deviation (U-R), and supination-pronation (S-P) movements of the wrist in terms of the horizontal (x-axis), vertical (y-axis), and rotational (z-axis) motions of a cross-shaped cursor projected onto a screen.

C. CONVOLUTION NEURAL NETWORK

Feature extraction is commonly used in EMG analysis. The features extracted should represent the activation level/pattern of the raw EMG signals and should also reduce the dimensions of the original data. However, these features are usually generated from statistics derived from stable time series that may fail to preserve the connections among multiple channels and other significant details. In an effort to excavate fully the information contained within EMG signals, we incorporated the raw signals (after filtering) of suitable window length direct input into a predictive model. At the same time, we used the CNN model, which has the capacity to learn general information from large quantities of data and to provide multiple outputs. In a previous study, we tested a variant of this method (CNN) for the purpose of hand gesture recognition in particular. The input and weights of the intermediate layers were calculated as arrays in the network. Our results showed that the classification accuracy was higher than other CNN structures on two open EMG datasets (NinaPro-DB2 and CapgMyo-DBa), which were measured at 73.5% and 91.7%, respectively.

The main structure of the network consisted of three (or four) convolution layers and two full connection layers,Rather than relying on hand- engineering features, the convolution layers have the capacity to learn to extract the necessary information from raw EMG signals and relate it to wrist movements. This information can then be decoded gradually along the cascaded layers. The pooling layer was introduced for the purposes of downsampling the features extracted time domain, eliminating redundant information, and increasing the reliability of the output. The final convolution layer required a special design; specifically, the size of convolution kernel had to equal the array length of the layer's input. Only in this way could the output of a hidden unit in this layer serve as a scalar variable. This variable was thus a design feature of the CNN structure that could contain all of the necessary information from the input time series. Lastly, the full connection layer provided the magnitude of each DOF of the wrist movement simultaneously. Rather than designing specific structures according to each individual DOF, we allowed the CNN model to acquire this knowledge itself.

D. DATA COLLECTION PROTOCOL

During the experiment, subjects were instructed to control the force of 3-DOF wrist movements based on feedback from the laser cursor. The amplitude and velocity of the cursor's movements were not strictly limited. Subjects were encouraged to expand the range of the movements without experiencing fatigue while maintaining a sufficient moving speed so that the trajectory of the cursor could be clearly observed. The contraction level was less than 50% maximum voluntary contraction. We designed ten regular movements that combined a maximum of 2-DOF. Before the experiment, the subjects were given the opportunity to familiarize themselves with the operation of the equipment. During the experiments, they were given sufficient rest time to prevent fatigue. The experiment of one session lasted about 20 min. Together with the wrist movements, the EMG signals were collected using eight wireless surface EMG electrodes (Trigno, Delsys Inc, USA). The electrodes were arranged equidistantly around the forearm using an armband of our design, the position was approximately one-third the length of the forearm near the olecranon. The EMG signals were collected at 2000 Hz and then filtered through a fourth-order Butterworth band pass filter (20–500 Hz) and a notch filter (50 Hz). The filtered EMG signals and wrist movement measurements all had mean values near zero that were normalized to create an identical distribution (i.e., with the standard deviation equal to one) before the training.

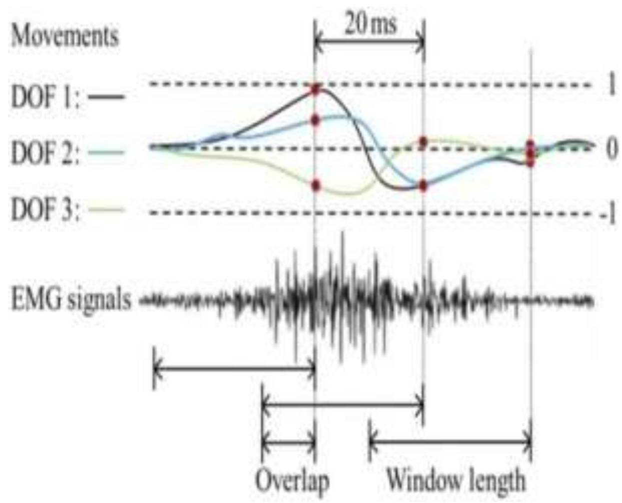

Fig. 3. Relationship between the multi-DOF movements and EMG signals. The values of the red dots at the ends of the windows represent the learning targets for EMG samples

MODULE 1: PROCESSING INPUT

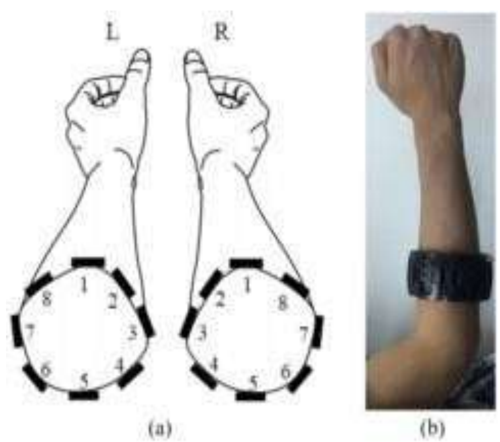

Fig.4. Positioning electrodes in forearm

DESCRIPTION:

The input has been sent by using sensor, From this the signal is detected. This methods to detect the signal from a human body is done by interfacing sensors and converting their signal values from analog to digital value and filter their noise using feature extraction. These data's are trained in CNN

MODULE 2: CNN CLASSIFIER

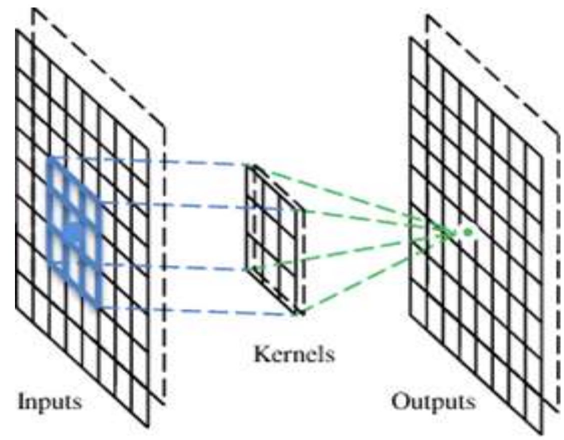

Fig.5.CNN classifier with middleware kernels

DESCRIPTION:

A CNN is a neural network with some convolutional layers (and some other layers). A convolutional layer has a number of filters that does convolutional operation. CNNs, like neural networks, are made up of neurons with learnable weights and biases. Each neuron receives several inputs, takes a weighted sum over them, pass it through an activation function and responds with an output. The whole network has a loss function and all the tips and tricks that we developed for neural networks still apply on CNNs.

MODULE 3:

RESULT INTERPRETATION

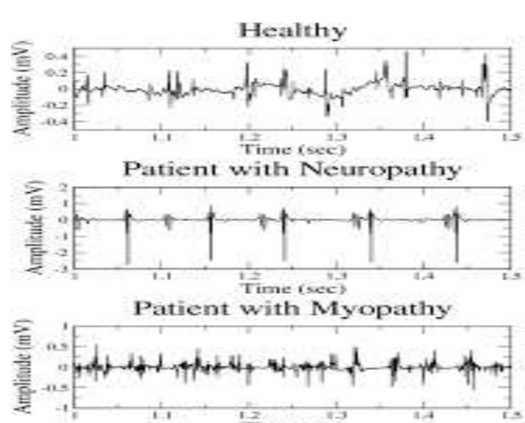

Fig.6. Comparison of healthy and defective persons

DESCRIPTION:

The last step, we compare the performance from two previous steps and make the conclusion. The accuracy of the experiments will show the performance of each technique in terms of values classification. Deep Learning or CNN techniques are the good algorithms that we can apply on the detect the signal from a human body is done by interfacing sensors and their signal values

MODULE 4: THRESHOLDING

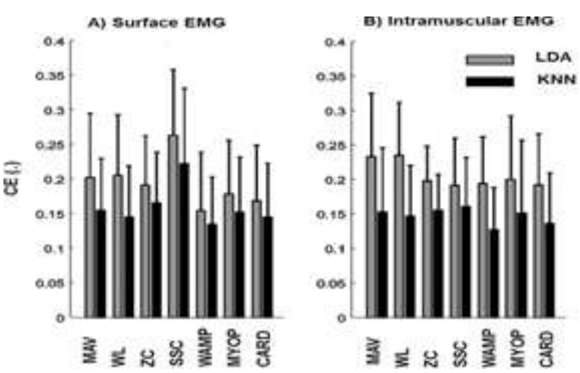

Fig.7.Bar graph of thresholding

DESCRIPTION:

Segmentation involves separating an image into regions (or their contours) corresponding to objects. We usually try to segment regions by identifying common properties. Or, similarly, we identify contours by identifying differences between regions (edges). The simplest property that pixels in a region can share is intensity. So, a natural way to segment such regions is through thresholding, the separation of light and dark regions. Thresholding creates binary images from grey-level ones by turning all pixels below some threshold to zero and all pixels about that threshold to one. (What you want to do with pixels at the threshold doesn't matter, as long as you're consistent. If g(x, y) is a thresholded version of f (x,

y) at some global threshold T. g is equal to 1 if f x(,

y) ≥ T and zero otherwise.

CONCLUSION:

In this paper, we report a preliminary attempt to decode simultaneous wrist movements into 3-DOF directly from raw EMG signals using a novel deep learning model (CNN). Rather than relying on hand-engineering features, this predictive model can automatically extract necessary information from special channels and then relate it to activities associated with each DOF. The accuracy of our model exceeds that of traditional regression methods such as SVR, especially in high adaptability level experiments. The results presented here demonstrate that a CNN model with the capacity for generalization can be established based on multi- subject training and can serve directly as a rough control for a new subject without further training.

Fine tuning further improved the model's adaptability to a given subject with only a brief training sequence. Furthermore, owing to hardware limitations (RAM of GPU), it is not currently feasible to train a DL model with significantly more layers and more complex structures. In future work, we will continue to collect EMG data from ever more subjects and to analyze thoroughly the individual differences among subjects. We also intend to apply this method to the simultaneous and proportional control of dexterous hand prostheses with multi-DOF and to similar devices.

REFERENCES:

[1] Akira Furui,Hideaki Hayasi and Toshio Tsuji , "A Scale Mixture- Based Stochstic Model of Surface EMG Signals With Variable Variances," Crit. Rev. Biomed. Eng., vol. 38, no. 4, pp. 305–345, 2019.

[2] Marcel H. Trabuco, Marcus V. C. Costa,Bruno Macchiavello and Franscisco Assis de O. Nascimento , "S-EMG Signal Compression in One- Dimensional and Two-Dimensional Approaches ," Sci. Transl. Med., vol. 6, no. 257, 2018, Art. no. 257ps12.

[3] YoungJae Song and Francisco Sepulveda, "A Novel Technique for Selecting EMG-Contaminated EEG Channels in Self-Paced Brain-Computer Interface Task Onset ," Biomed. Signal Process. Control, vol. 2, no. 4, pp. 275–294, 2018.

[4] Weichao Guo, Xinjun Sheng, Honghai Liu and Xiangyang Zhu , "Toward an Enhanced Human- Machine Interface for Upper-Limb Prosthesis Control With Combined EMG and NIRS Signals ," IEEE J. Transl. Eng. Health Med., vol. 4, 2017, Art. no. 2100508.

[5] Radhika Menon ,Gaetano Di Caterina, Heba Lakany, Lykourgos Petropoulakis, Bernard A. Conway and John J. Soraghan , "Study on Intearction Between Temporal and Spatial Information in Classification of EMG Siganls for Myoelectric Prosthesis," IEEE Sens. J., vol. 18, no. 16, pp. 6812–6821, Aug. 2017.

[6] Hideaki Hayashi, Akira Furui, Yuichi Kurita,Toshio Tsuji, “A Variance Distribution Model of Surface EMG Signals Based on Inverse Gamma Distribution ,” IEEE Trans. Biomed. Eng., vol. 64, no. 11, pp. 2575–2583, Nov. 2017.

[7] Ali H. Al-Timemy, Rami N.Khushaba, Guido Bugmann and Javier Escudero , “Improving the Performance Against Force Variation of EMG Controlled Multifunctional Upper-Limb Prosthesis for Transradial Amputees ,” Front Syst. Neurosci., vol. 9, 2016, Art. no. 162.

[8] Sirince Thongpanja, Angkoon Phinyomark,, Franck Quaine,Yann Laurillau,Chusak Limsakul and Pornchai Phukpattaranont, “Probability Density Functions of Stationary Surface EMG Signals in Noisy Environments ,” Front. Neurorobotics., vol. 8, 2016, Art. no. 22.

[9] Marina M.-C.Vidovic, Han-Jeong Hwang, Sebastian Amsuss, Janna M. Hahne, Dario Farina and Klaus-Robert Miller , “Improving the Robustness of Myoelectric Pattern Recognition for Upper Limb Prosthesis by Covariate Shift Adaptation ,” Expert Syst. Appl., vol. 40, no. 12, pp. 4832–4840, 2016.

[10] Giho Jang, Junhoon Kim, Sungon Lee and Youngjin Choi, “EMG-Based Continous Control Scheme With Simple Classifier for Electric-Powered Wheelchair ., vol. 22, no. 5, pp. 1395–1405, Sep. 2016.

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