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SEMG based HMI using ANN

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ABSTRACT

This paper present the use of hand gestures for human-computer interaction, this paper presents an approach to identify hand gestures using muscle activity separated from electromyogram (EMG) using ANN. To retain a constraint-free user's environment, EMG sensing is limited to three arm muscles. EMG signals are processed to attain parameters that are related to the muscles temporal activities. The attainment of these parameters through time constructs a unique signature for each particular gesture. Experimental investigation was carried out to examine the system's reliability in recognizing 6 arm gestures. The results show that the system can recognize the 6 gestures with a success rate of 98%. The advantage of such a system is that it is easy to train by a layer, and can easily be implemented in real time after the initial training

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INTRODUCTION

The standard computer interfaces such as keyboard or mouse are inherently driven by physical contacts (pressure) and movements of users. These physical interactions involve delicate and coordinated movements of upper limb, wrist, palm and fingers. On the contrary, there are the cases, in which some people are not apt to utilize the interfaces with their physical disabilities that have come from diseases such as spinal cord injury (SCI), paralysis, and amputation. In modern days like todays, they involve themselves in projects to restrain the e ongoing increase in inconvenience of the uses of the interfaces due to the disabilities

The alternatives, which modern technology has resolved to, to provide the access to a computing environment for people with the disabilities are direct contact devices with a physical keyboard, such as mouth-sticks and head-sticks. Downsides of these devices are in their inaccuracy and inconvenience in its usage. To overcome those problems, several bio signal based human-computer interfaces (HCIs) have become the new destination of the resolution, which have successfully emerged to extract a user's intention because these signals provide information related to body motion faster than other means (such as kinematics and dynamic interfaces)

Despite the success of the biosignal based HCI, few common standards for the performance evaluation has been established by researchers. They follow the same basic techniques in the development of interface; however, the standards vary greatly among them that it is hard for the people to compare the performance of the different interfaces

More and more researchers and practitioners in the fields of human-computer interaction and robotics emphasize the necessity for humanizing machine interaction, thus calling for more intuitive interfaces. Attaining this goal is dependent upon both software and hardware systems that can relieve.

Users from technical detail of their working environments. The user should be able to behave in a natural way and bring into action natural modes of expression such as gesture. Therefore, gesture and sign language have become a recent focus in advanced interface design. The growing attention that gesture-based interfaces have been receiving is due to- the large number of potential applications and activities that can be eased and improved when they are operated or dealt with in a natural manner. Existing intuitive or natural interfaces include Data-gloves and arm/hand goniometry. In these classes of approaches, the user wears bulky equipment that can constrain normal movement; furthermore, in cases involving actual handling of objects, Data-glove may not be appropriate. Alternative approaches include speech, video, and EMG, in formation processing systems. The current speech recognition technology is still not robust, especially outside controlled environments, under noisy conditions, and with multiple speakers. Video information acquisition is non-contact and thus does not impose any constraints on the user; however, obtaining detailed information about a motion is generally

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very difficult even when using multiple cameras. Consequently, researchers tend to limit the application domain. Moreover, visual information cannot estimate force, pressure, or efforts that are produced by the user's hand, which are important in interacting with the machines.EMG signals have been used in the medical engineering field in relation to the tracking of trajectories, successful application that has been in the market for more than tree decades is the EMG-driven control systems have taken a new direction. Several studies have suggested the use of EMG signals as a method of interaction with machines

This paper presents an EMG-based signal processing system that interprets hand gestures in automated Instrument control. Independently can become a tremendous challenge for persons with progressive neuromuscular disorders. While muscle weakness and limited range of motion presents the initial challenge, this is exacerbated by diminishing abilities that can make dynamic proportional control systems inaccessible. For persons with advanced conditions that have reached this point, EMG support machines is commonly considered to be the option of last resort. This is such a commonly held view in the field of rehabilitation technology that few rehabilitation technologists even consider it as a viable option. EMG activity is used extensively for prosthetic control and recently for computer control (Lippert, H., 2000), but its use for Automated Instrument (such as Coursers movement) has not found wide acceptance. This study demonstrates that EMG control system offers a viable means for persons with severely limited motor movement to independently control a Instrument by using an ANN, which offer many advantages over traditional control methods.

An EMG is a bioelectric signal generated by muscle use. The amplitude of an EMG can range from 0 to 10 mV (peak-to-peak) and the usable energy of the signal is limited to the 0 to 500 Hz frequency range. An EMG can be acquired on the skin near to the muscle by differential amplification in order to eliminate the noise signal. An EMG electrode should be placed between a motor point and the tendon insertion and along the longitudinal midline of the muscle. They are used extremity by people with both lower and upper high level spinal cord injury, muscular dystrophy. The aim of the intelligent instrument is to make instrument able to be controlled and navigated with the minimal interaction with the users, in order to enhance the quality of service for the handicaps. In our studies, we have designed and fabricated an automatic instrument with a signal processing section to recognize the motion commands from hand gesture and by using signal condition and microcontroller; it is used to control four mean articles for the benificitory of the spinal injured subjects.

Methodology:

2.1 Gesture selection:

For controlling an automated system, four different gestures are required. These gestures should be equally easy to perform and form pattern in the EMG signal which are as discriminative as possible.

These gestures should be equally easy to perform and form patterns in the EMG signal which are as discriminative as possible. Before the start and after the finish of each gesture, the hand should be situated in a posture called the home position, in which hardly any signal amplitude occurs. After testing over 20 different gestures the four gestures were selected as control signs since they seemed to fulfill the mentioned requirements best as shown in table I. The first gesture , Hand extension (gesture I), is a short and opening of the first, the second gesture , Hand Grasp (gesture 2) is performed by a short and very light pressing of the first. The motion of the wrist towards the outside is known as Wrist extension (gesture 3) and the fourth gesture selected Thumb Flexed towards inside is Know as Thumb Flexion (gesture 4).

The choice of the performing hand is not an issue since our experiments showed that both hands generate extremely similar EMG waveforms, except for unremarkable differences in overall amplitude. As most users opt for the right hand, the names and descriptions of the gestures refer to the right hand and have to be mirror-inverted for a left handed usage.

2.2System structure:

In this section the single processing steps of the system, from the recording of a gesture to the selection of option in HCI, are described. The EMG signal of the performing arm muscles is detected by electrodes connected to a sensor. In order to qualify the incoming raw signal for further processing the signal is preprocessed first. Next, the incoming patterns, which represent a gesture movement in the signal, are matched. To be able to distinguish patterns, the significant features of each pattern are first extracted. The resulting feature vector is used for the classification of the movement order. Finally, the control command briefed through the performed gesture is executed by the Microcontroller for operating the peripheral devices.

2.3Signal acquisition:

We used Surface EMG sensor which enables to record EMG signals of up to 6000 μV in an active range of 20 to 500Hz. For the recording of the EMG signal, only one pair of pre-gelled single Ag/AgCl electrodes was fixed on the skin of the system user's along Abductor Pollicies longus. Usually, each pair of electrodes is used to examine mainly one single muscle. Signal interferences of adjacent muscles, known as crosstalk, are normally undesirable. Since we used only one channel sensor for signal

acquisition it was necessary to examine several muscles simultaneously with one pair of electrodes. These observed muscles were mainly the flexor carpi radialis and the palmaris longus, both of which are responsible for wrist movements, as well as the flexor digitorum superficialis, which is used for finger movements. All three electrodes are situated in a line in the middle of the forearm parallel to the length of the forearm muscle fibers. By placing the first electrode near the wrist, it is possible to examine the muscles of the forearm between their tendon insertions and their motor points, which seems to be the best location for a constant measurement (Deluca, C.J., 2002). The reference electrode is placed in the middle. The sampling rate of the EMG signal in the system was set at 125 samples per second.

2.4 MUAPS using wavelets:

EMG signal is time series data. Therefore, it is not easy to infer operator's intension of motions from raw EMG signal; electrodes placed on a muscle, measure a superposition of single Motor Unit Action potentials (MUAPs), artifacts and background noise. Basic shapes of surface MUAPs can be represented by only a few wavelet functions (Nikolay, S. Stoykov, M. Madeleine, 2005). The clinically interesting features of the EMG signal are the number of active motor units and the MUAP waveform (Ping Zhou, W.Z. Rymer, 2003). Quantitative analysis in clinical electromyography (EMG) is very desirable; with the development of computer aided EMG equipment different methodologies in the time domain and frequency domain have been followed for quantitative analysis. Wavelet transform provides two dimensional time-frequency representation. Wavelet transform has the ability to localize in the statistics of non-stationary signals and it provides an alternative to short-time Fourier Transform (STFT) which uses a single analysis window. The wavelet transform uses short window at high frequency and long window at low frequencies. In the case of db4, WT coefficients at the highest-frequency scales provide high time-resolution of only four signal samples. This allows the db4 wavelet to effectively track the MUAP main spike transient signal at a time resolution that the STFT simply can't match (Earl Gosh, Richard Jhonson Baugh, 2002). In our work we have used db4 for four levels to decompose the signals (Muhammed Gambo Abdullahi,).

2.5 Feature extraction:

To be able to classify a performed gesture some distinctive features have to be found and taken from each matched pattern. Therefore several features were extracted, including common statistical feature like RMS, Entropy and standard deviation (Md. Belal Hossain).

2.6Pattern Recognition:

Artificial neural network (ANN) has been emerged as an important tool for pattern recognition mainly used in HCI researches (Barniv *et al*., 2005, Hiraiwa *et al*., 1990). One of the advantages of using ANN is that because ANN acts like a black box model, it does not require detailed information regarding to the system. In order to design the network (the black box) for the classification of EMG signals, a set of examples flow through the network. Then, the network adjusts its internal structure until it reaches a stable stage at which the outputs are considered satisfactory. After the successful training, the network is preserved and receives new input information, which have never seen before, and then the network processes the information to produce appropriate outputs. During the training stage, all subjects were instructed to get six different wrist motions in turn, and then the filtered EMG signals were extracted. Next, the network was trained using those six groups of wrist movements and desired network responses shown in Table 1.Its tuning was carried out by using a back propagation algorithm with a momentum approach (Dr. J. Subash Chandra Bose, *et al*., 2015).

2.7 Experimental setting:

We conducted a more comprehensive experiment with a total of 20 subjects. First of all, we collected personal information about the subjects, including age (average 21.85 year's) gender (09 females and 11 males), weight (Average: 52.15Kg) and performing hand (20 right hands, nil left hander).

The experiment consisted of two phases. Ten subjects participated in the first phase and for each subject, we recorded six gestures of hand position and total 60 gesture are taken from each gesture we have taken three feature values which was averaged and finally the average of 10 subject's feature were taken as a test samples. The remaining taken as a test samples. The remaining 10 subjects with 6 gestures of hand were taken as test samples, among these six gestures four gestures were selected as shown in Table-1.

For the data acquisition a proprietary SEMG acquisition system by Trident Tec Labs was used before placing the electrodes subject's skin was prepared by lightly abrading with skin exfoliate to remove dead skin that helps in reducing the skin impedance to less than 60 Kilo Ohm. Skin was also cleaned with 70% v/v alcohol swab to remove any oil or dust on the skin surface. In the second part of the experiment, the neural network was trained using the data from the subject and tested similarly. The architecture of the ANN consisted of two hidden layers and the 20 nodes for the two hidden layers were optimized iteratively during the training of the ANN. Sigmoid function was the threshold function and the type of training algorithm for the ANN was gradient descent and adaptive learning with

momentum with a learning rate of 0.05 to reduce chances of local min- ima. In the testing section, the trained ANNs were used to classify the VarianceRMS values of recordings that were not used in the training of the ANN to test the performance of the proposed approach. The ability of the network to correctly classify the inputs against known hand actions were used to determine the efficacy of the technique.

Class of the command	Desired network's response			
LEFT	1	0	0	0
RIGHT	0	1	0	0
UP	0	0	1	0
DOWN	0	0	0	1

Results:

Back propagation neural network was trained with four types of hand gesture Five set of experiments s. The result of the use of these normalized values to train the ANN using data from individual subjects showed easy convergence. The results of testing the ANN to correctly classify the test data based on the weight matrix generated using the training data is tabulated in table 1. The accuracy was computed based on the percentage of correct classified data points to the total number of data points. The classification accuracy was 97.5% for all the experiments.

Conclusion:

This paper has shown that an EMG signal can be effectively employed in human-machine neural interface. The presented EMG-based controlling interface is able to reliably recognize various hand gestures with a positive classification rate of over 97.5% even though we used only one single EMG sensor, in contrast to related work which is based on multiple EMG sensors. The good performance of the system was also reflected by the user's subjective ratings of the system's usability.

The EMG signal carries valuable information regarding then nerve system. It would be quite easy to transfer its use to application of different peripherals. Moreover, since the EMG signal can be used to sense isometric muscular activity, it is possible to detect motionless gesture or intention in the EMG signal. Consequently, there is a wide range of potential applications using EMG signal in human machine interfacing. However, to realize advanced applications, many issues still need to be resolved, including the development of algorithms for EMG-specific analysis, the extraction of relevant features, and the design of real-time classifiers with guaranteed accuracy, as discussed in this paper. Finally all the procedures have to be carried out by miniature portable device which consist of signal analysis and application in a single setup.

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