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EMG Signal Classification for Human Computer Interaction: A Review

Md. R. Ahsan
Electrical & Computer Engineering Department
Kulliyyah of Engineering, International Islamic University
Kuala Lumpur, Malaysia
E-mail: rezwanul.ahsan@yahoo.com
Tel: +60-36196-4000, Ext: 2841

Muhammad I. Ibrahimy
Electrical & Computer Engineering Department
Kulliyyah of Engineering, International Islamic University
Kuala Lumpur, Malaysia

Othman O. Khalifa
Electrical & Computer Engineering Department
Kulliyyah of Engineering, International Islamic University
Kuala Lumpur, Malaysia

Abstract

With the ever increasing role of computerized machines in society, Human Computer Interaction (HCI) system has become an increasingly important part of our daily lives. HCI determines the effective utilization of the available information flow of the computing, communication, and display technologies. In recent years, there has been a tremendous interest in introducing intuitive interfaces that can recognize the user's body movements and translate them into machine commands. For the neural linkage with computers, various biomedical signals (biosignals) can be used, which can be acquired from a specialized tissue, organ, or cell system like the nervous system. Examples include Electro-Encephalogram (EEG), Electrooculogram (EOG), and Electromyogram (EMG). Such approaches are extremely valuable to physically disabled persons. Many attempts have been made to use EMG signal from gesture for developing HCI. EMG signal processing and controller work is currently proceeding in various direction including the development of continuous EMG signal classification for graphical controller, that enables the physically disabled to use word processing programs and other personal computer software, internet. It also enable manipulation of robotic devices, prosthesis limb, I/O for virtual reality games, physical exercise equipments etc. Most of the developmental area is based on pattern recognition using neural networks. The EMG controller can be programmed to perform gesture recognition based on signal analysis of groups of muscles action potential. This review paper is to discuss the various methodologies and algorithms used for EMG signal classification for the purpose of interpreting the EMG signal into computer command.

Keywords: HCI, EMG, Neural Network, Hidden Markov Model, Bayes Network etc.

1. Introduction

Recently, a significant amount of effort has been dedicated in the field of HCI in the field of HCI for the development of user-friendly interfaces employing voice, vision, gesture, and other innovative I/O channels. In the past decade, studies have been widely pursued, aimed at overcoming the limitations of the conventional HCI tools such as keyboard, mouse, joystick, etc. One of the most challenging approaches in this research field is to link a human's neural signals with computers by exploiting the electrical nature of the human nervous system. More recently, there has been increasing interest in exploiting bioelectric signals such as EMGs, EEGs and EOGs for the purpose of devising new types of HCI. As the silver generation has been exponentially increasing, the social demands for the quality of life (QOL) also have been increasing proportionally. To improve the QOL of the disabled and the elderly, robotic researchers have been trying to combine the robotic techniques into the rehabilitation systems. However, since the robotic system needs to guarantee both the safety and reliability, many recent studies proposed the human-in-the-loop control system for considering user's intention. Since the human's information system is different from the machinery system, HCI is regarded as one of key technologies in the human-in-the loop control system (Moon et. al., 2004). To implement an HCI, the acquired and processed signals need to classify which is the difficult part of the system. The choice of classification methodology depends on the application field. In the field of HCI, the studies found that most of the classifiers are neural network based. This is because it has been used by many researchers in the past very widely as well as it has numerous advantages in the processing and classification of biosignals.

This paper first discussed about several types of non biosignal based devices/systems, their applications along with some advantages and weak points. Then the paper proceeds with different kind of methodologies used for EMG signal classifications in the field of HCI. Finally a summary table presented with brief properties of the classifier discussed in this paper.

2. Techniques used in HCI

2.1. Non-biosignal Approach

Several attempts have been done beside the use of biomedical signals to implement a convenient solution of HCI for the disabled persons. These devices are based on motor skills and still available to use. The "Tonguepoint" based on IBM Trackpoint, a pressure sensitive isometric joystick operated by user's tongue. The joystick provides cursor-control, while two switches (a bite switch and a manual switch located outside of the mouth) allow the user to consider left and right button selections (Salem et. al., 1997). Another commercially available device "Headmouse" (Website: http://orion.com/access/headmouse/index.htm), a pointing device, that that transforms head movement into cursor movement on the screen. This device device uses infrared distance measurement to measure the head motion. The wireless sensing technology employs infrared light to track a small disposable target (reflective accessory) that is placed on the user's forehead or glasses. The mouse pointer movement on the screen is then proportional to the user's head movement, which are used to trigger a switch through which the user can control various system functions. A specific problem with head mouse systems is the required motor skills. The mentioned approaches have potential disadvantages for some categories of users. For example, a user with cerebral palsy may not have the fine motor abilities in the tongue to operate the Tonguepoint device. Similarly, a user with spinal vertebrae fusion may not be able to turn his or her head, so the Headmouse would be of little benefit (Barreto et. al., 2000). Patients with severe multiple sclerosis and SCI have reduced range of neck motion causing difficulties during computer use through these type of devices (LoPresti et. al., 2003). Subjects with disabilities were also found to have longer reaction time, and spend more time trying to make fine adjustments to cursor position. Filtering and gain adjustment options in some of head-control systems might improve usability for some people with neck movement impairments. However, limitations of these systems have been demonstrated by practical experiments. It was also found that more adaptive techniques required to allow head control for automatic adjustment to the needs and abilities of a particular user. However, limitation of these systems have been demonstrated by practical experiments. It was also found that more adaptive techniques required to allow head control for automatic adjustment to the needs and abilities of a particular user. More severe problems with head control were mentioned in (Ortega R. et. al., 2004). A Head mouse system operates on the principle of a single switch. This allows the user to give single commands at the appropriate time and reduce the amount of user's head movements. However, a critical issue with this approach is its exact timing requirement, which often leads to increase head movement and spasticity; especially when the user is trying to work relative fast. Head movements indeed require considerable muscles and ligaments efforts and their overuse can cause injuries to the users (Surdilovic et. al., 2005).

Other more complex approaches have attempted to provide computer interface functionality requiring even fewer abilities from the potential users. A prominent example is the eye-gaze tracking interface approach. This principle patented by Mason K. A., (1969) is based on the observation that reflected light produces a bright spot (glint) on the cornea, which position can vary according to the change of eye-gaze direction. In the most common types of these systems, an infrared illuminator and video camera are used to obtain continuous images of the subject's eye. Application of digital image processing techniques allows the real-time isolation of two landmark reflections from the subject's eye: the reflection from its pupil and the smaller and brighter reflection from its cornea. Real-time determination of the centers of these reflections and their relative positions in the image captured by the camera is used to define the instantaneous orientation of the eye's line of gaze. The clicking operation in these systems has been attempted by assigning a "dwell latency" and executing a click whenever the cursor remains within a so-called "dwell neighborhood" for at least that amount of time. This clicking procedure, however, may result in false clicks if a user is simply staring attentively at a small area of the screen, a dilemma referred to as the "Midas Touch" problem (Jacob, 1991). Given their complexity and computational requirements, eye-gaze-tracking systems are comparatively expensive and require great attention and effort to achieve proper cursor control (Foulds et al., 1997).

The research using eye-gaze to create a usable HCI is active (Wang et. al., 2006), e.g., eye mouse. However, there is still no efficient interface being built up due to the inaccuracy of the eye-tracking technique and the Midas Touch problem. In (Bates et. al. 2002), a zooming-in interface has to be designed to compensate for the positional tolerance of eye tracking. Problem is the target size significantly affects the system performance. Despite some difficulties, an effort is made in this technology to make eye-gaze-tracking systems more portable (e .g. head-mounted version) (Barreto et. al., 1999). Although they provide the subject with the ability to quickly displace the cursor across the screen, is not easy to execute fine, small cursor movements in these systems. Furthermore, the stability of the cursor in a single screen position is limited. If the user changes position with respect to the plane of the screen during the use of the device, the calibration is lost and cursor position errors develop. Another weak point is, if the subject moves enough to shift his/her eye out of the field of vision of the camera, the operation of the system is disrupted. A comparative studies carried out by Barreto et. al., (1999), clearly indicates that the eye-gaze approach requires more strenuous and stringent control abilities for finer cursor movements. At present, some eye-gaze systems do attempt to compensate for the movement of the subject by using a pan-tilt camera, and adding a magnetic head tracking device to feed head position information and command compensatory movements to the camera, in real time. Results are improved with this addition, but unfortunately at the expense of added complexity and cost.

In recent years, vision-based hand gesture recognition has become a very active research theme because of its potential use in HCI. Vision-based gesture recognition is achieved by using video cameras, image processing and visual tracking algorithms. Advanced mouse emulators named Camera Mouse (Betke et. al., 2002) track users' movements with a camera focusing on various body features as target, such as tip of the user's nose, eyes, lips or fingers. Sophisticated pattern recognition software algorithms recognize the target pattern, determine motion parameters, and translate this information into motion of the mouse pointer on the screen. Initial experiments with the Camera Mouse have given encouraging results for subjects with relatively good muscle control abilities. It has proven to be user friendly because it requires no calibration or body attachments before and during its use. It is easily adaptable to serve specific needs of various disabilities, and it is especially suitable for children (e.g. with cerebral palsy). However, several problems were also observed during its experiments, such as drifts, loss of communication, slow communication rates etc (Betke et. al., 2002). People with insufficient muscles control, the Camera Mouse become quite ineffective. Nakanishi et. al. (1999) proposed a powered wheelchair controlled by the face directional gestures. But the gesture recognition required a high-speed image processing hardware and overall cost of system become very high. However vision based techniques require restricted backgrounds and camera positions and are suitable for a small set of gestures per formed with only one hand (Pavlovic et. al., 1997).

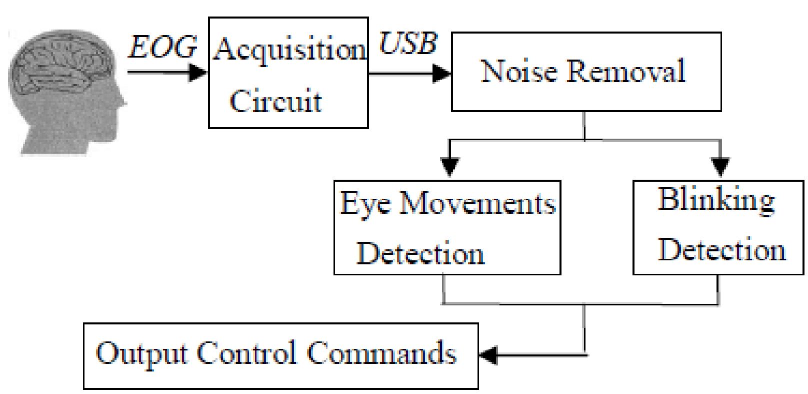
2.2. Biosignal Based Approach

2.2.1. EOG Signal Approach

Some biosignals have also been shown to be suited for the creation of a new communication interface between humans and computers. In this area the use of biosignals offer brand new possibilities when compared to the conventional, mostly audio-visually based HCI. Eye movements are arguably the most frequent of all human movements (Jonghwa Kim et al., 2008). In terms of our primary senses, the eye is one of the main subsystems of the body. The position of the eye directly relates with the visual information of interest. It is possible to provide very intuitive assistive device by using the position of the eye. It is possible to provide very intuitive assistive device by using the position of the eye. Position of the eye can be measured optically, mechanically, and electrically. The electrical method of measurement, the EOG, is the least invasive method of determining the eye position (Doyle et. al. 2006).

Eye movement research is of great interest in the study of neuroscience and psychiatry, as well as ergonomics, advertising and design. Since eye movements can be controlled volitionally, to some degree, and tracked by modern technology with great speed and precision, they can now be used as a powerful input device, and have many practical applications in HCI. EOG is one of the very few methods for recording eye movements that does not require a direct attachment to the eye itself (Qiuping Ding et. al., 2005). The ability of humans to visually follow the path of an object with the help of dynamic corrections is for the majority an easy task. The EOG is the electrical recording corresponding to the direction of the eye and makes the use of EOG for applications such as Man Machine Interface (MMI) that is very attractive. As most of the machines that need to be operated are computer controlled. MMI is synonymous to HCI (Kumar et. al., 2002).

Figure 1: Basic Block Component Diagram of HCI System based on EOG



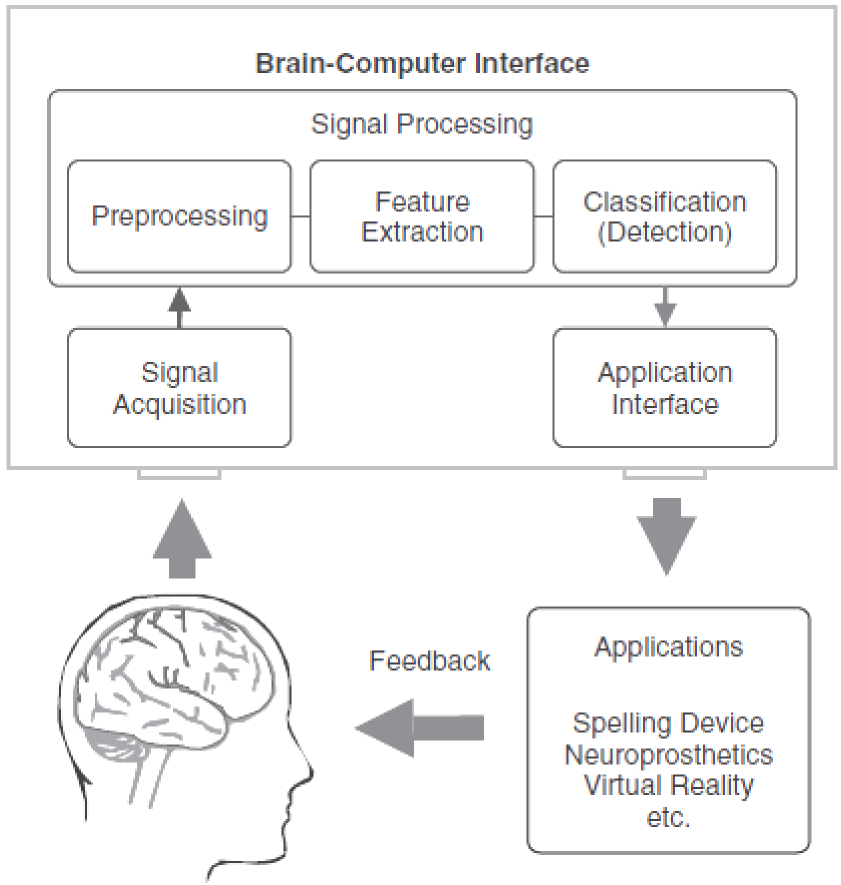
There are many ways used to measure the eye movement, some are more accurate than EOG, but most of them are far more expensive and bring much inconvenience and uncomfortable feeling to users. The EOG method is noninvasive, low-cost and easy to use. A study on the group of persons with severe disabilities shows that many of them have the ability to control their eye movements, which could be used to develop new HCI systems to help them communicate with other persons or control some special instruments. Furthermore, this application of EOG-based HCI could be extended to the group of normal persons for game or other entertainments. Compared with the EEG, EOG signals have the characteristics as follows: the amplitude is relatively high, the relationship between EOG and eye movements is linear, and the waveform is easy to detect (Zhao et. al., 2008).

To determine the applications of EOG based HCI, it is important to realize the limitations and the potential errors in the system. There may be several main sources of error that affect the accuracy of the HCI using EOG signals. There are several problems related to head and muscle movement interface, signal drift and channel crosstalk. Whether the user makes a choice or sits idle, there are always some unavoidable minor head movements (Kaufman et. al., 1993). It is, however, difficult to differentiate the gaze vector from EOG signals because the EOG signal is affected easily by a noise due to head movement (Kuno et. al., 1998). Some other factors that may affect HCI performance are angular displacement between head and torso, physiological defects, an individual perception of gaze point, and movement of the individual relative to a known reference point. The HCI using the EOG signal proposed by Krueger et al (2007) can be used for nearly every person except for totally locked-in patients. The reaction time of the cursor is very fast and the users made themselves familiar with the interface very easily. In a limited time the user was forced to increase the accuracy very fast. Furthermore, the game-like trial environment can create stressful situation on user and can measure user performance at certain time is an additional advantage. However good results could not be reproduced for every user and the learning curve can vary widely (Krueger et. al., 2007). The artificial stress situation blocked sometimes the performance of the system. The stability of the signal may increase significantly if the user allowed to do a free training. On the other hand a defined testing environment is needed for the HCI to characterize it and be comparable with other approaches (Birbaumer et. al., 2004). When maximum performance is desired it is discussable if an EOG system is still adequate. The user might also search for an eye tracking system which provides higher accuracy than EOG system. Yet the advantage of a simple system vanishes and either the hardware or the software computing power is a magnitude higher (Hiley et. al., 2006).

2.2.2. EEG Signal Approach

Numerous studies have shown that individuals with severe neuromuscular disabilities can learn to use a Brain Computer Interface (BCI), by modulating various features in their EEG (Wolpaw et. al., 2002). The BCI is an emergent multidisciplinary technology that allows a brain to control a computer directly, without relying on normal neuromuscular pathways (Dornhege et. al., 2007).

Figure 2: Structural components of a BCI System



The most important applications of the technology for the paralyzed people who are suffering from severe neuromuscular disorders, as BCI potentially provides them with communication, control, or rehabilitation tools to help compensate for or restore their lost abilities. Among various brain signal acquisition methods, the EEG is of particular interest to the BCI community (Wolpaw, 2002; Curran et. al., 2003; Vaughan et. al., 2003; Ebrabimi et. al., 2003). The EEG records the electrical brain signal from the scalp, where the signal originates from postsynaptic potentials, aggregates at the cortex, and transfers through the skull to the scalp (Fisch et. al., 1999). EEG based device that requires extracting raw EEG data from the brain and converting it to device control commands through suitable signal processing techniques. The cerebral electrical activities of the brain are recorded via the EEG using electrodes that are attached to the surface of the skull. These signals measured by the electrodes are amplified, filtered and digitized for processing in a computer where feature extraction is performed, classification is done and a suitable control command is generated (Gopi et. al., 2006).

EEG based BCI technology has seen much development in recent years. Specifically, EEG based BCI technologies that do not depend on peripheral nerves and muscles have received much attention as possible modes of communication for the disabled (Palaniappan, 2005).Various EEG phenomena, such as slow cortical potentials, P300 potentials, and mu and beta rhythm control can provide opportunities for severely disabled individuals to further interact with their environment . One of the popular phenomena utilized for BCI control is the modulation of mu (8-12 Hz) and beta (18-25 Hz) rhythms via motor imagery. Actual or imagined motor movements result in a de-synchronization (decrease in amplitude) of these rhythms over the sensorimotor cortex. Users are thus directly able to control a BCI by modulating the magnitude of these rhythms by switching between motor imagery tasks (Rasmussen et. al., 2006).

The EEG bears merits as it is noninvasive, technically less demanding, and widely available at relatively low cost. On the other hand, it also brings great challenges to signal processing and pattern recognition, since it has relatively poor signal-to-noise ratio and limited topographical resolution and frequency range (Wolpaw et. al., 2006). However non-invasive data acquisition makes automated feature extraction challenging. It is because the signals of interest are 'hidden' in a highly noisy environment. It was demonstrated that the spatial filtering operations improve the signal-to-noise ratio (Bufalari et. al., 2006). Unfortunately, the intensive training time (several months) involved for a user to gain a high degree of control (>80% accuracy) may be a deterrent for practical applications of BCIs such as prosthetic control and daily computer use for disabled individuals (Guger et. al., 2003).

2.2.3. EMG Signal Approach and Importance

Among these bioelectric signals, EMGs are considered to be the source of a new means of HCI, i.e. an alternative input mechanism. In fact, an input device developed using EMGs is a natural means of HCI because the electrical activity induced by the human's arm muscle movements can be interpreted and transformed into computer's control commands. Furthermore, EMGs can be easily acquired on the surface of human skin through conveniently attachable electrodes.

Compared to optical systems, EOG based systems provide favored possibilities for mouse pointer control, and are practical and valuable for people with SCI. However, their complex learning and calibration procedures present the main limitations and require further development (Surdilovic, 2005). On the other hand, one of the major limitations of BCI systems is the high potential for EMG contamination. EEG signals originate in the neurons of the brain and have to propagate through the skull and the pericranial muscles in order to reach the surface electrodes. Because the EEG signals are small in amplitude (5–300 μV), the EEG biopotential amplifiers are designed to incorporate high amplification (Taberner et. al., 1998). Thus, any muscle movement on the head or neck can produce a large noise contamination from the corresponding EMG signal. From an application standpoint, this is a big inconvenience to a user, especially if the user has a condition such as cerebral palsy. Most BCI researchers have tried their best to eliminate any EMG artifacts, especially eye blinks and neck movements (Wolpaw et. al., 1994; Pfurtscheller et. al., 1996).

The EEG is a noninvasive monitoring method of recording brain activities on the scalp (Millan et. al., 2004). However, signals acquired via this method represent the massed activities of many cortical neurons; they also provide a low spatial resolution and a low signal-to-noise ratio (SNR). Invasive monitoring methods, on the other hand, capture the activities of individual cortical neurons in the brain (Wessberg et. al., 2000). However, many fundamental neurobiological questions and technical difficulties need to be solved (Nicolelis, 2001), and extensive training is required for interface methods based on brain activities (Cheng et. al., 2002). Signals generated because of body motion at the level of peripheral nervous system can be detected by an ENG (Cavallaro et. al., 2003) and an EMG (Chu et. al., 2006). However, ENG-based interfaces have limitations with respect to the SNR, dimensions, and drifts: that is, damage to the neural tissue (Bossi et. al., 2006) and continued differential motion of the electrode within the fascicle cause a reduction in the SNR and a gradual drift in the recorded nerve fiber population (Lawrence et. al., 2004). Whereas, EMG signals can be measured more conveniently and safely than other neural signals. Furthermore, this noninvasive monitoring method produces a good SNR. Hence, an EMG-based HCI is the most practical with current technology.

EMG measures electrical currents that are generated in a muscle during its contraction and represent neuromuscular activities. EMG signals can be used for a variety of applications including clinical applications, HCI and interactive computer gaming. Moreover, EMG can be used to sense isometric muscular activity which does not translate into movement (Park et. al., website: http://melab.snu.ac.kr/Research/melab/doc/HCI/muscleman_paper.pdf). This makes it possible to classify subtle motionless gestures and to control interfaces without being noticed and without disrupting the surrounding environment. On the other hand, one of the main difficulties in analyzing the EMG signal is due to its noisy characteristics. Compared to other biosignals, EMG contains complicated types of noise that are caused by, for example, inherent equipment noise, electromagnetic radiation, motion artifacts, and the interaction of different tissues. Hence, preprocessing is needed to filter out the unwanted noises in EMG. This difficulty becomes more critical when resolving a multiclass classifying problem. In most previous works, therefore, multi-channel EMG sensors are used at the same time to detect relevant EMG patterns by a combined signal analysis. In this case, however, users suffer from the inconvenience of carrying many cabled electrodes (Jonghwa et. al., 2008).

In human-centered solutions such as a gesture-based interface, the system customarily compensates for individual differences between users to produce a consistent pattern-recognition rate no matter who is using the system. However, in the case of security, you can take advantage of user differences to prevent unauthorized users. You could also do this by monitoring EMG signals corresponding to typical computer command sequences. The EMG signals have different signatures depending on age, muscle development, motor unit paths, skin-fat layer, and gesture style. The external appearances of two peoples' gestures might look identical, but the characteristic EMG signals are different. In terms of fun applications, the video game industry constantly needs quick, flexible interfaces. New input devices such as the Xbox controller are pushing the limits by increasing the complexity of numerous physical buttons and sticks manipulated simultaneously. However, it is possible to map multiple muscle groups to different actions to distribute this complexity across the body. This would require training for proficiency, but the net result would be a whole new gaming experience (Wheeler et. al., 2003).

In the past three decades, myoelectric control has attracted more and more attention for its application in rehabilitation and human-computer interfaces. In myoelectric control systems, hand gestures are often used for controlling peripheral equipments. Hand gestures are captured by the means of surface electromyography (SEMG), by sensors which measure the activities of the musculature system (Weir, 2003; Chen et. al., 2007). Accurate recognition of the user's intent on the basis of the measured SEMG signals are the key problem in the realization of myoelectric control. From early 1970', researchers have studied the classification of hand motions such as finger flexion-extension, wrist flexion-extension and supinationpronation by sensing the activities of upper arm muscles. However, although the recognition rates have reached above 90 percent in the recent research work, there are still many problems that need to be solved for realizing practical applications of myoelectric control (Chen et. al., 2007).

Hand gestures involve relative flexure of the user's fingers and consist of information that is often too abstract to be interpreted by a machine. An important application of hand gesture recognition is to improve the quality of life of the deaf or non-vocal persons through a hand-gesture to speech system. Another major application is in rehabilitation engineering and in prosthesis. Some of the commonly employed techniques in hand recognition include mechanical sensors (Pavlovic et. al., 1997), vision based systems (Rehg et. al., 1994) and the use of EMG (Koike et. al., 1996) EMG has an advantage of being easy to record, and it is non-invasive. SEMG is the electrical manifestation in contracting muscles activity and closely related to the muscle contraction and thus an obvious choice for control of the prosthesis. Since all these muscles present in the forearm are close to each other, myoelectric activity observed from any muscle site comprises the activity from the neighbouring muscle as well, referred to as cross-talk. The cross-talk problem is more significant when the muscle activation is relatively weak (subtle) because the comparable signal strength is very low. Extraction of the useful information from such kind of SEMG becomes difficult mainly due to the low signal to noise ratio. At low level of contraction, EMG activity is hardly discernible from the background activity. To identify the small movements and gesture of the hand, there is need to identify components of SEMG originating from the different muscles (Naik et. al., 2008).

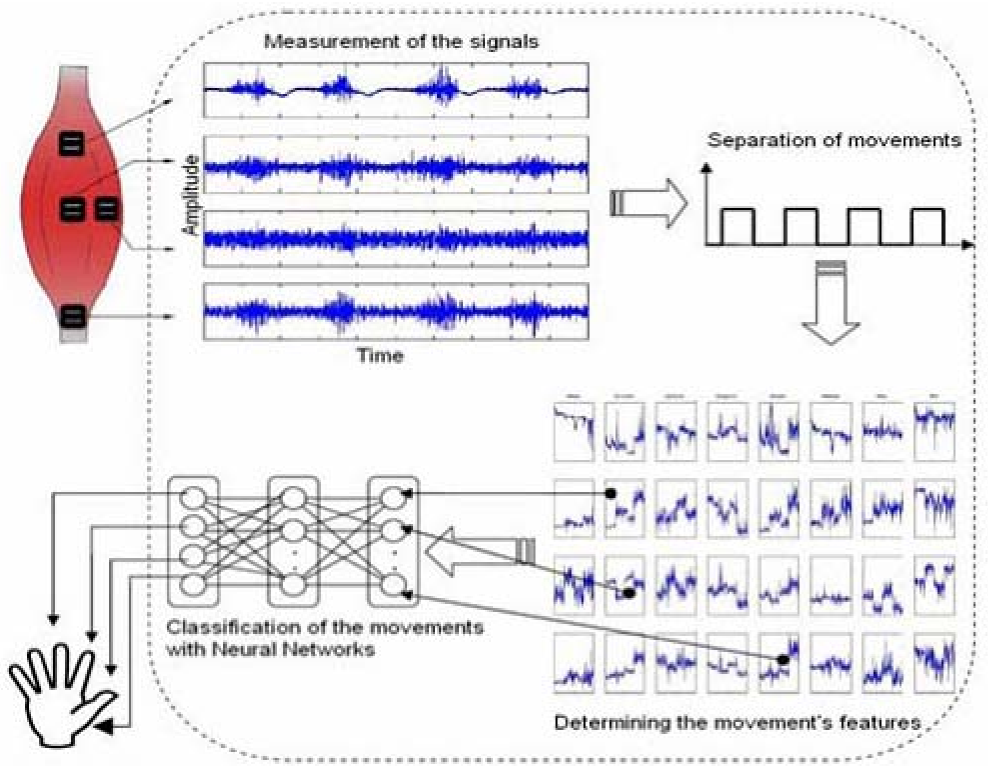
3. EMG Classification Méthodologies for HCI

Some artificial intelligence (AI) techniques mainly based on neural networks have been proposed for processing and discriminating EMG signal. Neural network is a computing technique that evolved from mathematical models of neurons and systems of neurons. During recent years, neural networks have become a useful tool for categorization of multivariate data. Even some of the cases, the neural network with other AI e.g. Fuzzy, Hidden Markov Model (HMM), Bayes yields very good performance.

3.1. Artificial Neural Network

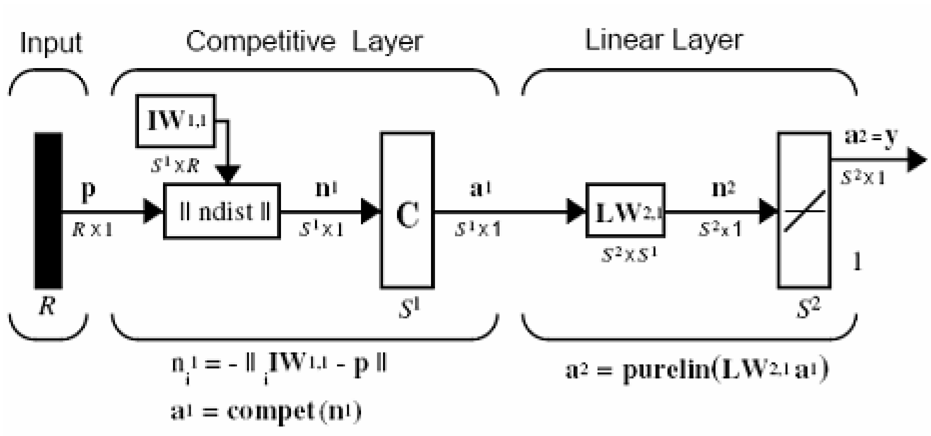
In 1993, William Putnam et. al. (Putnam et. al., 1993) proposed a real-time computer control system based on neural network for pattern recognition of the EMG from user's gestures. The system consists of two modes of communication are derived from the EMG. The first mode is a continuous control signal, proportional to muscular exertion which control computer software objects such as sliders or scroll bars. The second communication mode is gesture recognition. This allows the computer to make discrete choices such as menu selections or slider direction by executing different gestures. Single Layer Perception (SLP) structure was trained by Widrow-Hoff LMS algorithm. Whereas, a backpropagation algorithm was utilized to train Multi-Layer Perception (MLP) structure. Feature vector comprise with AR model parameters. Although 95% accuracy in classification was achieved, it is felt that a system utilizing both bicep and tricep data, along with a more robust classifier is warranted to accommodate users with disabilities who are unable to perform such clearly defined tasks as studied at the present time. Another prominent attempt is EMG controlled 2-dimensional pointer invented by Rosenberg (1998), which is known as Biofeedback Pointer. This graphic input device controlled by wrist motion. Moving the wrist causes the pointer to move in that direction. The pointer detects the EMG signals of four of the muscles used to move the wrist. These are interpreted by a neural network which is trained for each user. The Biofeedback Pointer's simple neural network is computationally inexpensive, but with the side effect of a reduction in accuracy which is compensated for by using four EMG sensors. Instead of using special hardware to train the device, the training is performed by requiring the user to follow the pointer's motion on the screen. During training period, the network calculated for 8 times with offset 0 to 448ms for finding out least error network. The reason behind this is to minimize the reaction time delay regarding user's motion. The main problem with the current training is that the user's motions may not adequately synchronize with the cursor.

Figure 3: The main steps of online classification of hand movement using EMG signals



G. Tsenov et. al. (2006) discovered that the classification performance of hand and finger movements depends significantly upon feature extraction, which is very important to improve considerably the accuracy of classification. They described the identification procedure, based on EMG patterns of forearm activity using various Neural Networks models. After comparison between different intelligent computational methods of identification, they gained best classification result (nearly 93% using 2-channel data) using MLP other than Radial Basis Function (RBF) or Learning Vector Quantization (LVQ). In the time domain, features like: Mean Absolute Value (MAV), Variance (VAR), Waveform Length (WL), Norm, Number of Zero Crossings, Absolute Maximum, Absolute Minimum, Maximum minus Minimum and Median Value (Med) are some of extracted features. Relevant features will lead to high and accurate classification rates. However, in practice, determination of relevant features is very difficult. One year later, Kyung Kwon Jung et. al. (2007) came with stronger classifiers that would help to implement the HCI. They proposed a method of pattern recognition of EMG signals of hand gesture using spectral estimation and neural network. Proposed system is composed of the Yule-Walker algorithm and the Learning vector quantization (LVQ). The use of the Yule-Walker algorithm is to estimates the power spectral density (PSD) of the EMG signals. LVQ is a method for training competitive layers in a supervised manner. A competitive layer automatically learns to classify input vectors. However, the classes that the competitive layer finds are dependent only on the distance between input vectors. If two input vectors are very similar, the competitive layer probably will put them in the same class. There is no mechanism in a strictly competitive layer design to say whether or not any two input vectors are in the same class or different classes. The experiment verified that EMG signals produced by hand gestures are reliably classified by proposed system with a success rate of about 78%.

Figure 4: LVQ Network Architecture



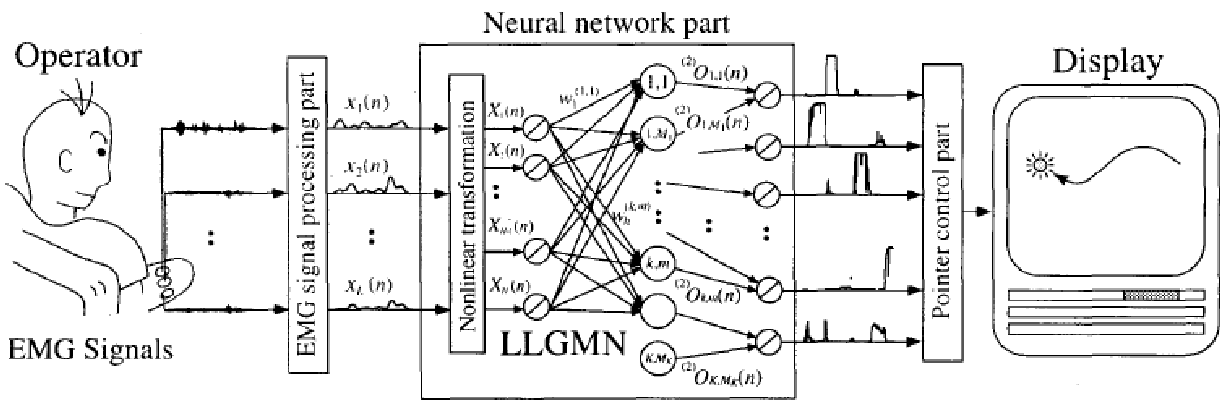
3.2. Back-Propagation (BP) based Neural Network

Back-propagation Neural Network (BPN) algorithm applied to EMG based mouse cursor control system as a man-machine interface by Itou et. al. (2001). They used neural network with three inputs, two hidden layer and one output layer which achieved 70% rate of recognition. Any muscle can be used, mouse cursor can be operated using a leg too, whereas, muscle fatigue may appeared for long time use. In 2007, Naik et. al. applied BPN to overcome the drawback of the standard Artificial Neural Network (ANN) architecture by augmenting the input hidden context units, which give feedback to the hidden layer, thus giving the network an ability of extracting features of the data from the training events. The data was divided into subsets of training data, validation, and test subsets. One fourth of the data was used for the validation set, one-fourth for the test set, and one half for the training set. The four RMS EMG values were the inputs to the ANN. The outputs of the ANN were the different isometric hand action RMS values. The overall accuracy was reported 97%, but the number of hand gesture identification was restricted to three. One year later Ganesh R Naik et. al. (2008) proposed more improving identification of various hand gestures using multi run ICA of SEMG with back-propagation learning algorithm based ANN classifier. They reported that only ICA is not suitable for SEMG due to the nature of SEMG distribution and order ambiguity. They also showed that a combination of the mixing matrix and network weights to classify the SEMG recordings in almost real-time. Their results indicate an overall classification accuracy of 99% for all the experiments and can be used for the classification of different subtle hand gestures. However, BPN cannot realize high learning and discrimination performance because the EMG patterns differ considerably at the start and end of the motion even if they are within the same class. Whereas, Eman et. al. in 2008, applied HMM of surface EMG algorithm that facilitates automatic SEMG feature extraction and ANN are combined for providing an integrated system for the automatic analysis and diagnosis of neuro-muscle disorders. The number of input nodes is 312 using the 4 HMM features for 78 SEMG segments and the number of outputs is two output nodes. In each model, each subject was characterized by 312 feature vector calculated using HMM. Every vector is considered as one training pattern, so there are 52 training patterns and 55 testing set. ANN architectures with three layers (input layer, hidden layer and output layer) were used. The ANN architectures are expressed as strings showing the number of inputs, the number of nodes in the hidden layers and two output nodes. They achieved the best correct classification rate was 90.91% for 80 hidden layers.

3.3. Log-Linearized Gaussian Mixture Network (LLGMN) and Probabilistic Neural Network (PNN)

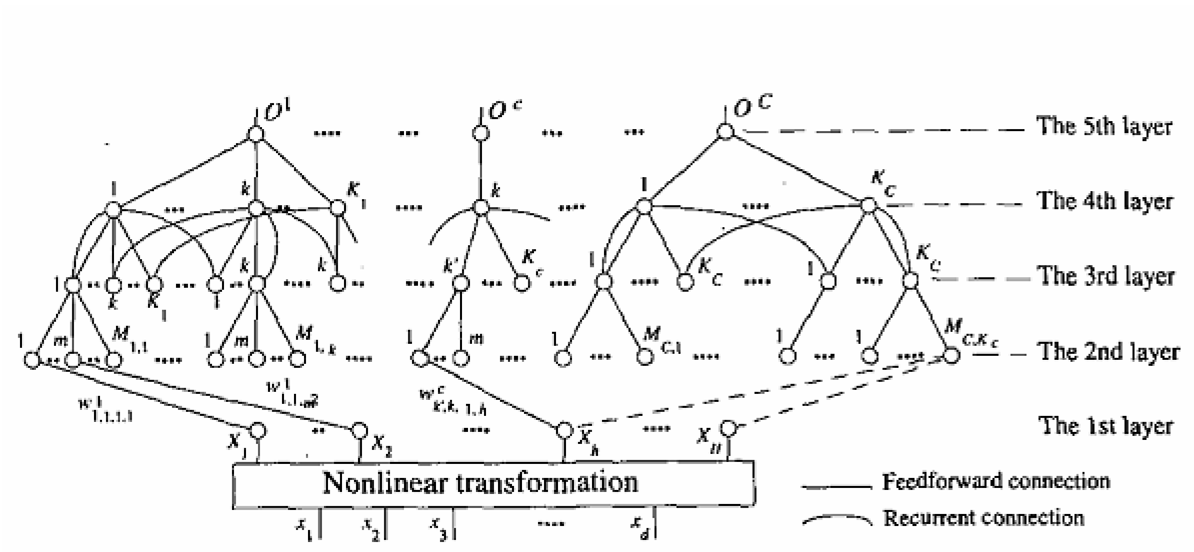
The neural network has to estimate the probability that the pointer will move to each base direction, so that the heavy learning calculation and the huge network structure are not necessary. Neural network is used as a pointer controller in the prototype system. This system can adapt itself to changes of the EMG patterns according to the differences among individuals, different locations of the electrodes, time variation caused by fatigue or sweat, and so on. Fukuda et. al. (1999) presented an EMG controlled pointing device using a neural network and developed a prototype system. This system uses the information on the EMG signals for pointer control. The operator's intended direction of the pointer movement and its velocity are estimated from the EMG signals, and natural interaction can be expected using this information. In the proposed method, a several numbers of base directions are set on the computer display, and the operator's intended direction is estimated from the probability that the pointer will move to each base direction. The neural network used to estimate the probability of the pointer movement to each base direction. This way it is possible to avoid heavy learning calculation and the huge network structure. In the neural network part, the Log-Linearized Gaussian Mixture Network (LLGMN) proposed by Tsuji et al.(1995) is used.

Figure 5: Structure of the prototype system based on LLGMN classifier



The LLGMN can acquire the log-linearized Gaussian mixture model through learning and calculate the posteriori probability of the pointer movement to each base direction based on this model. The probability density function is expressed by the weighted sum of the Gaussian components. It enables the LLGMN to learn the complicated mapping between the operator's EMG patterns and the pointer movement. Before the operation, the LLGMN must be trained the nonlinear mapping between the EMG patterns and the pointer movement. Then the LLGMN can estimate the pointer movement based on the statistical model. The accuracy improves depending on the increase of the number of the base directions, although a large number of the base directions require much longer learning time. The error becomes large when the desired direction differs from the base direction. However, this method can control the pointer in an arbitrary direction, but accuracy of the estimated direction was not so high to the intention of the operator. Furthermore, if the pointer is allowed to move in all directions from the current position, the number of moving directions will be infinite. To overcome this, Tsuji et al. (1995) has therefore proposed Recurrent Log- Linearized Gaussian Mixture Network (R-LLGMN) based on a continuous density hidden Markov model (CDHMM) (Chen Xiang, 2007). This network uses recurrent connections added to the units of LLGMN in order to discriminate a time sequence of the signals with high accuracy. Osama Fukuda et al. (2003) proposed a new EMG-controlled omni-directional pointing device using R-LLGMN. In the proposed pointing device, an arbitrary direction of pointer movement is represented using a combination of finite base directions. Since the neural network utilized in this system only estimates the probability for each base direction, it may lead to avoid a heavy learning calculation and a huge network structure. The probability of pointer movements in each base direction can be estimated by R-LLGMN using probability theory. Their results showed that the direction errors improved remarkably. According to Nan Bu et. al. (2004), a probabilistic neural network (PNN) provides a stochastic perspective of pattern discrimination; it has been proven to be efficient for complicated data such as bioelectric signals. They proposed programmable gate array (FPGA) implementation of a PNN, with which system on chip (SoC) design of a bioelectric human interface device. This PNN called a LLGMN, which estimates the posterior probability based on a Gaussian

Figure 6: The Structure of R-LLGMN



mixture model (GMM) and the log-linear model. Although weights of the LLGMN correspond to a nonlinear combination of the GMM parameters, such as the mixture coefficients, mean vectors, and covariance matrices, constraints on the parameters in the statistical model are relieved in the LLGMN. Therefore, a simple learning algorithm can be derived, and the LLGMN is expected to have high performance in the case of statistical pattern discrimination. The LLGMN has been successfully applied to pattern discrimination of bioelectric signals, e.g., EMG and EEG and has been further used to develop various human interface applications like prosthetic device control, an EMG-based pointing device. The problems include non-trivial in cases of implementation of larger and more complicated neural networks, and more hardware efficient algorithms are required.

3.4. Fuzzy Mean Max Neural Network (FMMNN)

Jong-Sung Kim et. al. (2004) applied fuzzy mean max neural network (FMMNN) as a classifier for online EMG mouse that controls computer cursor. Also, stochastic values such as integral absolute value were used as features for an appropriate classification of the intended wrist motions. He interpreted 6 predefined wrist motions to left, right, up, down, click and rest operation. Here, Difference Absolute Mean Value (DAMV) extracted from the EMG signals is used as the input vectors in learning and classifying the patterns. The commands for controlling mouse cursor movements can then be generated in accordance with these classified patterns. The DAMV is calculated for each window of data according to the following equation:

$$DAMV = \frac{1}{N-1}\sum_{i-2}^{N}\left|x(i) - x(i-1)\right| \qquad (1)$$

where x is data available within a window and N is window size on the time frame .

Pattern recognition rate for each wrist motion reported as above 90%. The average recognition rate of 97% shows a promise that it can be used as an efficient means of HCI.

3.5. Radial Basis Function Artificial Neural Network (RBFNN)

A novel method for online estimation of human forearm dynamics using a second-order quasi-linear model is presented by Farid Mobasser et al. (2006). Human arm dynamics can be used for human body performance analysis or for control of human-machine interfaces. The proposed method uses Moving Window Least Squares (MWLS) to identify dynamic parameters for a limited number of operating points in a variable space defined by elbow joint angle and velocity, and the electromyogram signals collected from upper-arm muscles. The dynamic parameters for these limited points are then employed to train a Radial Basis Function Artificial Neural Network (RBFNN) to interpolate/extrapolate for online estimation of arm dynamic parameters for other operating points in the variable space. The model parameters are identified for a limited number of points using a MWLS estimation method. The limited number of points is justified as in contact applications the arm workspace and movement is relatively small and slow. The RBFANN has the advantage of minimum memory usage for function approximation and has been used significantly for interpolation. One major factor in parameter error is the stochastic nature of EMG signals. The online estimation accuracy may be improved by changing the neural network input quantization level, and the use of more sensors for each muscle for more accurate representation of Muscle Activation Levels.

3.6. Other Methodologies used

3.6.1. Hidden Markov Model

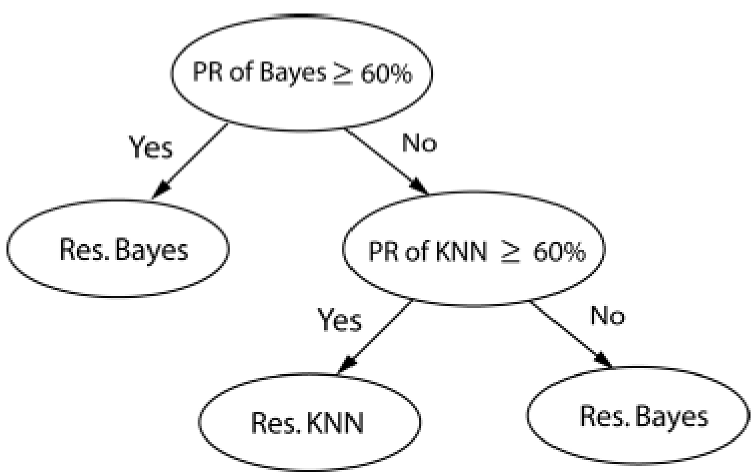
Wheeler (2003) introduced an approach of designing and using neuroelectric interfaces for controlling virtual devices. Hand gestures are used to interface with a computer instead of manipulating mechanical devices such as joysticks and keyboards. EMG signals are non-invasively sensed from the muscles used to perform these gestures. These signals are then interpreted and translated into useful computer commands. Among the most common methods like Short Time Fourier Transform (STFT), Wavelets, Moving Average, Auto-Regression (AR) Coefficients, they found moving average is the best and simplest for feature space. The pattern recognition method employed was a HMM. The ability to naturally interface with a computer allows for humans to manipulate any electrically controlled mechanical system. In addition to wearable computing applications it can also applied interfaces to robotic arms, mobile robots for urban rescue, unmanned aircraft drones, robotic exoskeletons, and space suit interfaces. There are also side benefits to using EMG signals for control in long duration space missions. However, one of the side effects of living in a zero gravity environment for extended periods is muscle atrophy. Another disadvantage is wet electrodes caused unintentional misplacement that greatly degraded our recognition performance. Standard EMG dry electrodes incorporated into a sleeve alleviated this problem but then raised significant reliability issues in signal sensing. Chan et. al. (2005) used HMM in their research for feature discrimination. Using 4-channel of SEMG signal, they achieved a classification accuracy of 87%.

3.6.2. Bayes Network

Alsayegh (2000) presented an EMG-based human-machine interface system that interprets arm gestures in the 3-dimensional (3D) space. Gestures are interpreted by sensing the activities of three muscles, namely, anterior deltoid (AD), medial deltoid (MD), and biceps brachii (BB) muscles. The problem of gesture classification is carried out in a framework of the statistical pattern recognition. The processing of the EMG signals utilizes the temporal coordination activity of the monitored muscles to identify a particular gesture. The classification procedure is carried out by constructing successive feature vectors for each gesture. These feature vectors describe the gesture's temporal signature. This type of classification is referred to as the context-dependent classification, which is carried out in this study within the framework of Bayes theorem. The overall success rate is 96%. It was observed that the structured type movements have a higher classification success rate than the pointing (simple) movements. The main reason that structured type gestures have a better classification rate is due to the clear coordination of the muscular activities. However, The input method described there is of course non-standard, since it does not make use of a keyboard or a mouse – it is, however, inappropriate for helping disabled persons, since it still requires control over the hands. In 2007, Xiang Chen et. al. implemented multiple hand gesture recognition along with a 2-D accelerometer for mobile HCI.

Feature extraction is carried out to reduce the data dimensionality while preserving the signal patterns which help to differentiate between the gesture classes. In their research, MAV, the ratio of two MAVs, and fourth-order AR model coefficients are used in the formation of the feature vectors. The accelerometer feature vector consists of the mean absolute values. The Linear Bayesian Classifier is trained with the feature vectors to distinguish the different gesture actions from each other. Due to their low computational complexity and stable recognition performance, classical linear classifiers are well suited for real-time gesture analysis and real life implementation. It was reported that the combination of accelerometers and SEMG sensors provided higher classification accuracy, especially for gesture sets including wrist motions, than the approaches using only the accelerometers or SEMG sensors. The development of an EMG based interface for hand gesture recognition is presented by Jonghwa Kim et al. (2008). For realizing real-time classification assuring acceptable recognition accuracy, they introduced the combination of two simple linear classifiers (K-nearest neighbor (KNN) KNN and Bayes) in decision level fusion. As the duration of the classification process is an essential factor for the efficiency of a real-time system, it is required to apply two comparatively simple and thus fast algorithms: the K-nearest neighbor (KNN) classifier and the Bayes classifier. Despite their simplicity these algorithms generally provide proportionally good results. The KNN classifier, which belongs to the non-parametric statistical classifiers, rates a pattern by regarding the most similar labeled training samples. For this purpose, the distances (e.g. Euclidean distance) between the feature vector of the current pattern and the feature vectors of each training sample are calculated. Beforehand, all vectors are generally normalized. The number of adjacent samples which are taken into account is defined by the parameter k. In our pattern recognition system, they considered the five nearest neighbors.

Figure 7: Decision Tree of Classifier Combination



The presented EMG-based controlling interface is able to reliably recognize various hand gestures with a positive classification rate of over 94% even though only one single EMG sensor used, in contrast to related work which is based on multiple EMG sensors. 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

4. Discussion

It can be found from the review that ANN plays an important role in the classification of EMG signal for further interpretation to computer command. By last decades, many researchers successfully applied various algorithm based neural network. Even though, it can be realized that, neural network as well as composition with other artificial intelligent as for example Fuzzy logic, HMM yields satisfactory recognition results. The neural network with Yule-Walker algorithm and the Learning vector quantization (LVQ) reported a success rate of about 78%. Effective classification accuracy can also be obtained from BP based neural network but problem is that it cannot realize high learning and discrimination performance because the EMG patterns differ considerably at the start and end of the motion even if they are within the same class. PNN with LLGMN is efficient for complicated data such as bioelectric signals. The accuracy improves depending on the increase of the number of the base directions, although a large number of the base directions require much longer learning time. 97% average recognition rate reported by using FMMNN. HMM are popular dynamic classifiers in the field of speech recognition. HMM are perfectly suitable algorithms for the classification of time series. HMM are not much widespread within the HCI community but the studies revealed that they were promising classifiers for HCI systems. A summary of major classification methods is given in the table below.

Table 1: Summary of major methods used for EMG classification in the field of HCI

Classifier Used	Researcher	Description
Artificial Neural Network (ANN)	Putnam et. al. (1993)	• AR model parameters based feature vector for Neural Network • 95% accuracy in classification was achieved • More robust classifier required for persons with disabilities
	Rosenberg (1998)	• One layer feed-forward neural network • Performance yields 14% according to Fitt's law • More sophisticated neural network and better training methods required for future improvement
	Tsenov et. al (2006)	• Both time and frequency domain features used • MLP based model yield best result compare to RBF and LVQ • Classification accuracy can be as hi as 98% using 4-channel data set, computational time becomes double. • It is hard to determine complete set of relevant discrimination features
	Kyung Kwon Jung et. al (2007)	• Yule-Walker algorithm based AR model for spectral estimation • 4^{th} order AR model parameters as input for LVQ neural network • Competitive layer for learning and linear layer for classifying for LVQ • Classifier success rate is about 78% • There is no mechanism in a strictly competitive layer design depending on input vector classes
Backpropagation Neural Network (BPNN)	Itou et. al. (2001)	• New type of EMG based mouse developed • 70% recognition rate in mouse cursor • Not applicable for long term use • Limited to 4 directions and drag action absent
	Naik et. al. (2007, 2008), Eman M. El-Daydamony et. al. (2008)	• ICA based signal extraction method used • Temporal decorrelation source separation (TDSEP) algorithm based ICA gives 97% separation efficiency than others • RMS value of each signal used to form feature vector as input to neural network • Combination of the mixing matrix and network weights to classify the sEMG recordings in almost real-time • Number of hand gesture identification was restricted to three and six
Log-Linearized Gaussian Mixture	Tsuji et. al. (1995) Fukuda et. al. (1999)	• LLGMN for creating LLGM model through learning and calculating the posteriori probability of pointer movement in each base direction depending on EMG patterns

Network (LLGMN)		• Higher discrimination performance can be achieved than other neural network • The direction of pointer movement is achieved by output of neural network • The accuracy of pointer movement depends on number of learning data and the accuracy of estimated direction depends on number of base directions
Recurrent LLGMN	Tsuji et. al. (2003) Fukuda et al. (2004)	• Continuous density hidden Markov model • (CDHMM) based Recurrent LLGMN • Finite base direction assumed which leads to avoid heavy learning calculation and huge network structure • Higher accuracy for the discrimination of time sequence of signal • Direction errors improved remarkably
LLGMN based Probalistic Neural Network (PNN)	Nan Bu et. al. (2004)	• FPGA implementation of PNN, LLGMN • HCI on FPGA chip much more portable and compact • Classification rate of hardware is 97.9%, more than software • Shortage of memory for hardware language • Processing speed needs to improve
Fuzzy Mean Max Neural Network (FMMNN)	Jong-Sung Kim et. al. (2004)	• Stochastic values such as integral absolute value were used as features • Six distinctive wrist motions can be classified well • Difference Absolute Mean Value (DAMV) extracted from the EMG signals is used as the input vectors in learning and classifying the patterns • Pattern recognition rate of each wrist motions is above 90%, whereas average recognition rate yield 97% • 4 channel raw EMG signal used • It is important to extract appropriate feature vector for the classifier
Radial Basis Function Artificial Neural Network (RBFNN)	Farid Mobasser et al. (2006)	• Moving Window Least Squares (MWLS) estimation method used to identify limited number of operating points. • RBFNN is trained using limited points and is utilized for interpolation/extrapolation for online estimation of arm dynamic parameters • Parameters error found because of stochastic nature of EMG signals • Estimation accuracy can be improved by changing neural network input quantization level and more sensors for each muscle
Hidden Markov model (HMM)	Wheeler (2003), Chan et al. (2005)	• Moving average selected for feature space as it is best and simplest • HMM has inherent ability to deal with spurious misclassification • During classifier training, HMM provides large computational savings compared to MLP • Error rates depends on sleeve position, sweating, skin moisture, length of time that electrodes were worn, fatigue • Astronauts required further training to overcome muscle atrophy for long term staying in a zero gravity environment • Reported that the used methodology does not vary adaptively • Further improvement would required in model correcting adaptation and calibration stage
Bayes Network	Alsayegh, Xiang Chen et. al (2007), Jonghwa Kim et al. (2008)	• Reported that structured type movements have higher classification success rate than pointing movements • Common time domain and frequency domain features extracted • K-Nearest Neighbour (k-NN) classifier added with Bayes to obtain good result • Addition of accelerator meter with EMG sensors cany increase the classification rate 5-10% • Feature selection is important for better classification and increasing number of features does not always produce good result • Average classification rate reported was over 94% • Small discrepancies can result major differences in EMG signal as well as degrade the performance of classifier

5. Conclusion

Use of standard interface to operate computer is inappropriate for the persons suffering severe physical disability. This is because it requires reliable use of hand movements. Developing of HCI using different biosignals will help to improve the QOL of the disabled persons. EMG signal is one of the prominent out of other biosignals having valuable information regarding nerve system. This review paper focused on the algorithms and methodologies used for classifying EMG signals in the field of HCI. It can be concluded that the neural network dominating the classification of EMG for HCI development. There are still huge possible way to work for the disabled people by improving HCI and making it more natural use to them. Beside neural network, there are several artificial intelligent using of which may yield remarkable humanizing of HCI.

References

[1] Alsayegh O.A., 2000. “EMG-based human-machine interface system,” *Multimedia and Expo, 2000. ICME 2000. 2000 IEEE International Conference on*, vol. 2, pp. 925 – 928.

[2] Barreto A. B., Scargle S. D., Adjouadi M., 2000. “A practical EMG-based human-computer interface for users with motor disabilities,” *Journal of Rehabilitation Research and Development*, vol. 37(1), pp. 53-63.

[3] Barreto A. B., Scargle S. D., and Adjouadi M, 1999. “A Real-Time Assistive Computer Interface for Users with Motor Disabilities,” ACM *SIGCAPH Computers and the Physically Handicapped*, pp. 6-16.

[4] Bates R., Istance H., 2002. “Zooming interfaces!: enhancing the performance of eye controlled pointing devices,” *Proceedings of the fifth international ACM conference on Assistive technologies Assets’02*, 119-126.

[5] Betke M., Gips J. and Flemeing P, 2002. “The camera Mouse: Visual Tracking of Body Features to Provide Computer acess for People With Severe Disabilities”, *IEEE Transaction on Neural Systems and Rehabilitation Engineering*, Vol. 10, No.1, pp. 1-10.

[6] Birbaumer N., Strehl U., and Hinterberger T., 2004. “Future FES Systems - Brain-Computer Interfaces for Verbal Communication,” *Neuroprosthetics - Theory and Practice*, K.W. Horch, G.S. Dhillon, Singapore: World Scientific Publishing Co. Pte. Ltd., pp. 1146-1157.

[7] Bossi S., Micera S., Menciassi A., Beccai L., Hoffmann K. P., Koch K. P., and Dario P., 2006. "On the Actuation of Thin Film Longitudinal Intrafascicular Electrodes," *Proceedings in The First IEEE/RAS-EMBS International Conference on Biomedical Robotics and Biomechatronics*, pp. 383-388.

[8] Bufalari S., Mattia D., Babiloni F., Mattiocco M., Marciani M. G., Cincotti F., 2006 “Autoregressive spectral analysis in Brain Computer Interface context,” *Engineering in Medicine and Biology Society, 2006. EMBS '06. 28th Annual International Conference of the IEEE*, pp. 3736 – 3739.

[9] Cavallaro E., Micera S., Dario P., Jensen W., and Sinkjaer T., 2003. "On the intersubject generalization ability in extracting kinematic information from afferent nervous signals," *IEEE Transactions on Biomedical Engineering*, vol. 50, pp. 1063-1073.

[10] Chan A., Kevin B., 2005. “Continuous Myoelectric Control for powered protheses using Hidden Markov Models,” *IEEE Transactions on Biomedical Engineer*, Vol. 52, pp. 123- 134.

[11] Chen Xiang, Zhang Xu, Zhao Zhang-Yan, Yang Ji-Hai, Lantz Vuokko, Wang Kong-Qiao, 2007. Multiple Hand Gesture Recognition Based on Surface EMG SignalBioinformatics and Biomedical Engineering, 2007, *ICBBE 2007, The 1st International Conference* on, pp. 506 – 509.

[12] Cheng M., Gao X. R., Gao S. G., and Xu D. F., 2002. "Design and implementation of a brain-computer interface with high transfer rates," *IEEE Transactions on Biomedical Engineering*, vol. 49, pp. 1181-1186.

[13] Chu J. U., Moon I., and Mun M. S., 2006. "A real-time EMG pattern recognition system based on linear-nonlinear feature projection for a multifunction myoelectric hand," *IEEE Transactions on Biomedical Engineering*, vol. 53, pp. 2232-2239.

[14] Curran E. A. and Strokes M. J., 2003. "Learning to control brain activity: A review of the production and control ofEEGcomponents for driving brain– computer interface (BCI) systems," *Brain Cognition*, vol. 51, pp. 326– 336.

[15] Dornhege G., Millan J., Hinterberger T., McFarland D., and Muller Eds. K.-R., 2007. "Toward Brain Computer Interfacing. *Cambridge,MA*: MIT Press.

[16] Doyle T. E., Kucerovsky Z., Greason W. D., 2006. "Design of an Electroocular Computing Interface", *Electrical and Computer Engineering, 2006. CCECE '06. Canadian Conference* on, pp. 1458-1461.

[17] Ebrahimi T., Vesin J. M., and Garcia v, 2003. "Brain–computer interface in multimedia communication," *IEEE Signal Process. Mag.*, vol. 20, no. 1, pp. 14–24.

[18] Eman M. El –Daydamony, Mona El- Gayar and Fatma Abou- Chadi, 2008. "A Computerized System for SEMG Signals Analysis and Classification," *National Radio Science Conference, 2008. NRSC 2008*, pp. 1-7.

[19] Fisch B. J., 1999. *Fisch & Spehlmann's EEG Primer*. Amsterdam, The Netherlands: Elsevier.

[20] Foulds R., Arthur J., and Khan A., 1997. "Human Factors Studies in Eye Movements Related to AAC Head Movement Studies," *Rehab. R&D 1996 Progress reports*, vol. 34, pp. 155-156.

[21] Fukuda O., Arita J. and Tsuji T., 2003. "An EMG-Controlled Omnidirectional Pointing Device Using a HMM-based Neural Network," *Neural Networks, 2003. Proceedings of the International Joint Conference* on, vol. 4, pp. 3195- 3200.

[22] Fukuda O., Tsuji T., Kaneko M., 1999. "An EMG controlled pointing device using a neural network Systems," *Man, and Cybernetics, IEEE SMC '99 Conference Proceedings. 1999 IEEE International Conference* on, vol. 4, pp. 63 – 68.

[23] Gopi E.S., Sylvester Vijay R., Rangarajan V., Nataraj L., 2006. "Brain Computer Interface Analysis using Wavelet Transforms and Auto Regressive Coefficients," *Electrical and Computer Engineering, 2006. ICECE '06. International Conference* on, pp. 169 – 172.

[24] Guger C., Edlinger G., Harkam W., Niedermayer I., and Pfurtscheller G., 2003. "How many people are able to operate an EEG-based brain-computer interface (BCI)?," *IEEE Trans. Rehab. Engng*, vol 11(2), pp. 145-147.

[25] Hiley J.B., Redekopp A.H. and Reza Fazel-Rezai, 2006. "A Low Cost Human Computer Interface based on Eye Tracking," *Proc. 28th Annu. IEEE EMBC*, New York, pp 3226 – 3229.

[26] Itou T., Terao M.; Nagata J., Yoshida M., 2001. "Mouse cursor control system using EMG," Engineering in Medicine and Biology Society, 2001. Proceedings of the 23rd Annual International Conference of the IEEE, vol. 2, pp. 1368 – 1369.

[27] Wolpaw J. R. and McFarland D. J., 1994. "Multichannel EEG-based brain-computer communication," *Electroencephalography and Clinical Neurophysiology*, vol. 90, no. 6, pp. 444-449.

[28] Jacob R. J., 1991. "The use of eye movements in human-computer interaction techniques: what you look at is what you get," *ACM Trans Inform System*, vol. 9(3), pp. 152-62.

[29] Jonghwa Kim, Stephan Mastnik, Elisabeth André, 2008. "EMG-based hand gesture recognition for real-time biosignal interfacing," International Conference on Intelligent User Interfaces, Proceedings of the 13th international conference on Intelligent user interfaces, pp. 30-39.

[30] Jong-Sung Kim, Huyk Jeong, Wookho Son, 2004. "A new means of HCI: EMG-MOUSE, Systems," *Man and Cybernetics, 2004 IEEE International Conference on*, vol. 1, pp. 100 – 104.

[31] Kaufman A.E., Bandopadhay A., Shaviv B.D., 1993. "An eye tracking computer user interface," Virtual Reality, 1993. Proceedings., *IEEE 1993 Symposium on Research Frontiers* in, pp. 120-121.

[32] Koike Y., and Kawato M.. 1996. "Human Interface Using Surface Electromyography Signals," *Electronics and Communications in Japan (Part III: Fundamental Electronic Science)*, vol. 79(9), pp. 15–22.

[33] Krueger T.B., Stieglitz T., 2007. "A Naive and Fast Human Computer Interface Controllable for the Inexperienced - a Performance Study," *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE*, pp. 2508-2511.

[34] Kumar D., Poole E, 2002. "Classification of EOG for human computer interface," Engineering in Medicine and Biology, 2002. 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society] EMBS/BMES Conference, 2002. Proceedings of the Second Joint, vol 1, pp. 64 – 67.

[35] Kuno Y., Yagi T., and Uchikawa Y., 1998. "Development of Eye Pointer with Free Head-Motion," *Proc. of IEEE Int'l Conf. on Engineering in Medicine and Biology Society*, pp. 1750-1752.

[36] Kyung Kwon Jung; Joo Woong Kim; Hyun Kwan Lee; Sung Boo Chung; Ki Hwan Eom, 2007. "EMG pattern classification using spectral estimation and neural network," *SICE, 2007 Annual Conference*, pp. 1108 – 1111.

[37] Lawrence S. M., Dhillon G. S., Jensen W., Yoshida K., and Horch K. W., 2004. "Acute peripheral nerve recording characteristics of polymer- based longitudinal intrafascicular electrodes," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 12, pp. 345-348..

[38] LoPresti E.F., Brienza D.M., Angelo J., and Gilbertson, 2003. "Neck Range of Motion and Use of Computer Head Control," *Journal of Rehabilitation Research and Development*, Vol 40, N0. 3, pp. 199-212.

[39] Mason K.A., "Control Apparatus Sensitive to Eye Movement", 1969. *U.S. Patent 3-462-604-1969*

[40] Millan J. D., Renkens F., Mourino J., and Gerstner W., 2004. "Noninvasive brain-actuated control of a mobile robot by human EEG," *IEEE Transactions on Biomedical Engineering*, vol. 51, pp. 1026-1033.

[41] Mobasser Farid, Hashtrudi-Zaad Keyvan, 2006. "A Method for Online Estimation of Human Arm Dynamics," *Engineering in Medicine and Biology Society, 2006. EMBS '06. 28th Annual International Conference of the IEEE*, pp. 2412 – 2416.

[42] Moon I., Lee M., Mun M., 2004. "A novel EMG-based human-computer interface for persons with disability," Mechatronics, 2004. ICM '04. *Proceedings of the IEEE International Conference on*, pp. 519 – 524.

[43] Naik G.R., Kumar D.K., Weghorn H., 2007. "Performance comparison of ICA algorithms for Isometric Hand gesture identification using Surface EMG Intelligent Sensors," *Sensor Networks and Information, 2007. ISSNIP 2007. 3rd International Conference* on, pp. 613 – 618.

[44] Naik G.R., Kumar, D.K., Palaniswami M., 2008. "Multi run ICA and surface EMG based signal processing system for recognising hand gestures," *Computer and Information Technology, 2008. CIT 2008. 8th IEEE International Conference* on, pp. 700 – 705.

[45] Nakanishi S., Kuno Y., Shimada N. and Shirai Y., 1999. "Robotic Wheelchair Based on Observations of Both User and Environment,", *Proc. of IROS 99*, pp. 912-917.

[46] Nan Bu, Hamamoto T., Tsuji T., Fukuda, O., 2004. "FPGA implementation of a probabilistic neural network for a bioelectric human interface," *Circuits and Systems, 2004. MWSCAS '04. The 2004 47th Midwest Symposium* on, vol. 3, pp. 29-32.

[47] Nicolelis M. A. L., 2001. "Actions from thoughts," *Nature*, vol. 409, pp. 403-407.

[48] Ortega R., 2004. "Unusal Acess Methods," Proceedings CSUN's 19th Annual International Conference "Technology and Persons with Disabilities", Los Angeles.

[49] Palaniappan R., 2005. "Brain Computer Interface Design Using Band Powers Extracted During Mental Tasks," *Neural Engineering, 2005. Conference Proceedings. 2nd International IEEE EMBS Conference* on, pp. 321 – 324.

[50] Park D. G., and Kim H. C., "Muscleman: Wireless input device for a fighting action game based on the EMG signal and acceleration of the human forearm." *[http://melab.snu.ac.kr/Research/melab/doc/HCI/muscleman_paper.pdf]*.

[51] Pavlovic V. I., Sharma R., and Huang T. S., 1997. "Visual interpretation of hand gestures for human-computer interaction," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 19, no. 7, pp. 677-695.

[52] Pfurtscheller G, Flotzinger D, Pregenzer M, Wolpaw JR, McFarland D., 1996. "EEG-based brain computer interface (BCI)". *Med Progr Technol*, 21.

[53] Putnam, W. Knapp, R.B., 1993. "Real-time computer control using pattern recognition of the electromyogram," *Engineering in Medicine and Biology Society, 1993. Proceedings of the 15th Annual International Conference of the IEEE*, pp. 1236-1237.

[54] Qiuping Ding, Kaiyu Tong, Guang Li, 2005. "Development of an EOG (Electro-Oculography) Based Human-Computer Interface," *27th Annual International Conference of the Engineering in Medicine and Biology Society, IEEE-EMBS 2005*, pp. 6829 – 6831.

[55] Rasmussen R.G., Acharya S., Thakor N.V., 2006. "Accuracy of a Brain-Computer Interface in Subjects with Minimal Training," *Bioengineering Conference, 2006. Proceedings of the IEEE 32nd Annual Northeast*, pp. 167 – 168.

[56] Rehg J. M., and Kanade D. T., 1994. "Vision-based hand tracking for human-computer interaction," *IEEE Workshop on Motion of Non-Rigid and Articulated Objects*, 16–22.

[57] Rosenberg, R., 1998. "The biofeedback pointer: EMG control of a two dimensional pointer, Wearable Computers," *Digest of Papers. Second International Symposium* on 19-20 Oct. 1998, pp. 162 – 163.

[58] Salem C, Zhai S., 1997. "An isometric tongue pointing device," *Proceedings of CHI'97*, March 22-27.

[59] Surdilovic T., 2005. "A Fuzzy Mouse Cursor Control System for Users with Spinal Cord Injury", 2005, *Master's Thesis*, Georgia State University.

[60] Taberner A. M., Barreto A. B., 1997. "Real-time signal processing towards an EEG-based human-computer interface," *Proceedings of the 1997 Florida Conference on Recent Advances in Robotics*, Miami, FL; 1997 . p . 56-60. & In 1998. Webster JG, editor. Medical instrumentation: application and design, 3rd Ed . Boston : Houghton Mifflin Company.

[61] Tsenov G., Zeghbib A.H., Palis F., Shoylev N., Mladenov V., 2006. "Neural Networks for Online Classification of Hand and Finger Movements Using Surface EMG signals," *Neural Network Applications in Electrical Engineering, 2006. NEUREL 2006. 8th Seminar* on On, pp. 167-171.

[62] Tsuji T., Bu N., Fukuda O., Kaneko M., 2003. "A Recurrent Log-Linearized Gaussian Mixture Network," *IEEE Transactions on Neural Network*, vol. 14, no. 2, pp. 304-316.

[63] Tsuji T., Ichinobe H., Fukuda O. and Kaneko M., 1995. "A Maximum Likelihood Neural Network Based on a Log- Linearized Gaussian Mixture Model," *Proceedings of IEEE International Conference on Neural Networks*, pp. 2479- 2484.

[64] Vaughan T. M., 2003. "Guest Editorial: Brain–computer interface technology: A review of the second international meeting," *IEEE Trans. Neural Syst. Rehabil. Eng*., vol. 11, no. 2, pp. 94–109.

[65] Wang, H., Chignell, M., Ishizuka, M. 2006. "Empathic tutoring software agents using real-time eye tracking," *In Proceedings of the 2006 symposium on Eye tracking research & applications ETRA'06*, pp. 73-78.

[66] Website: http://orin.com/access/headmouse/index.htm [Last visited 17-05-09]

[67] Weir R., 2003. "Design of artificial arms and hands for prosthetic applications," *In Standard Handbook of Biomedical Engineering & Design*, M. Kutz, Ed. New York: McGraw-Hill, 2003, pp.32.1–32.61.

[68] Wessberg J., Stambaugh C. R., Kralik J. D., Beck P. D., Laubach M., Chapin J. K., Kim J., Biggs J., Srinivasan M. A., and Nicolelis M. A. L., 2000. "Real-time prediction of hand trajectory by ensembles of cortical neurons in primates," *Nature*, vol. 408, pp. 361-365.

[69] Wheeler K.R., 2003. "Device control using gestures sensed from EMG, Soft Computing in Industrial Applications," 2003. SMCia/03. *Proceedings of the 2003 IEEE International Workshop* on, pp. 21 – 26.

[70] Wheeler K.R., Jorgensen C.C., 2003. "Gestures as input: neuroelectric joysticks and keyboards," *Pervasive Computing, IEEE*, vol. 2, issue 2, pp. 56-61.

[71] Wolpaw J. R., Loeb G. E., Allison B. Z., Donchin E., do Nascimento O. F., Heetderks W. J., Nijboer F., Shain W. G., and Turner J. N., 2006. "BCI meeting 2005—Workshop on signals and recordingmethods," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 138–141.

[72] Wolpaw J.R., Birbaumer N., McFarland D.J., Pfurtscheller G., and Vaughan T.M., 2002. "Brain-computer interfaces for communication and control," *Electroenceph. Clin. Neurophysiol*., vol. 113, no. 6, pp. 767–791.

[73] Xiang Chen, Xu Zhang, Zhang-Yan Zhao, Ji-Hai Yang, Lantz, V., Kong-Qiao Wang, 2007. "Hand Gesture Recognition Research Based on Surface EMG Sensors and 2D-accelerometers," *Wearable Computers, 2007 11th IEEE International Symposium* on, pp. 11 – 14.

[74] Yun Liu, Zhijie Gan, Yu Sun, 2008. "Static Hand Gesture Recognition and its Application based on Support Vector Machines," Software Engineering, Artificial Intelligence, Networking, and Parallel/Distributed Computing, 2008. SNPD '08. Ninth ACIS International Conference on, pp. 517 – 521.

[75] Zhao Lv, Xiaopei Wu, Mi Li, Chao Zhang, 2008. "Implementation of the EOG-Based Human Computer Interface System," *Bioinformatics and Biomedical Engineering, 2008. ICBBE 2008. The 2nd International Conference* on, pp. 2188 – 2191.