A Machine Learning approach to aid Paralysis patients using EMG signals

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Abstract – This research work focuses on hand movement classification from Electromyography (EMG) signals using Machine learning algorithms and the use of EMG signals for the human-human interface is presented. EMG signals are generated when an electric potential of the muscles changes after receiving signals from the brain due to contraction or expansion of muscles. The EMG signals have been collected by connecting electrodes to a person's arm and they are recorded using the BYB spike recorder app. Features are extracted from these signals and a dataset is obtained using these features. Hand movements of the person using this dataset are classified using various algorithms like KNN, SVM, Naïve Bayes, Decision tree (DT). All algorithms have offered promising accuracy around 90%, except KNN whose accuracy was 60%, thus can be used to control movements of people with disabilities by Human-human interface.

Keywords: EMG Signals, Feature Extraction, Machine learning, Human-human interface

1 Introduction

Our body uses electricity to control and communicate with other parts of the body. When we want to move any body part, our brain sends signals via neurons to the muscles of that part of the body, and changes in the electric potential of the muscles brought about by these neurons result in muscle contraction. When we contract a muscle, it is a result of many muscle fibers firing action potentials and changing shape. This electrical activity can be recorded and put to use. The signals that are generated due to responses from the brain and contraction or expansion of muscles as a result of it are referred to as EMG signals. The amplitudes of surface electromyography (EMG) signals can be used to control hand or arm movement [1]. EMG signals are generated only when a person moves his hand on his own, that is when there is the involvement of the brain as well as muscle movement. If any other person moves the hand of a person, there is only contraction and expansion of muscles and no involvement of the brain, therefore EMG signals are not generated.

Electromyography (EMG) is the procedure to assess the health of muscles and nerve cells that control them. EMG signals have been widely used for the diagnosis of neuromuscular disorders, prosthetics, human-machine interface control, and human movement tracking [2]. The electrical activity of the muscles in response to the nerve's stimulation of muscles is studied and disorders are identified. Paralysis is one such disorder where patients cannot make the necessary movement of muscles [3]. It happens because the messages between the brain and muscles cannot pass properly. Neuromuscular diseases affect muscle and nerve systems and they degrade the function of skeletal muscles.

The recent advancements in EMG signal processing and analysis techniques have the potential to be assistive to the disabled and elderly people who can make limited movements. However, in practice classification of EMG signals is difficult because they have non-linear and time-varying characteristics. Various pattern recognition algorithms are used in EMG signal processing. The study of EMG signal processing, Feature extraction, Classification techniques helps in developing an EMG-based Human-Machine Interface system [4].

The paper is organized as follows. The associated works related to Feature extraction from EMG signals, their classification using machine learning algorithms, human-computer interaction, and human-machine interaction are detailed in Section 2. Section 3 contains the System model, Section 4 contains Implementation and Results. This paper focuses on bringing about human-human interaction.

2 Associated Works

Before describing the proposed method we have given a broad survey related to associated works of feature extraction and classification of EMG signals and those of providing aid to people with disability with the usage of EMG signals. There has been a significant amount of work involving the use of EMG signals to carry out experiments on muscles and their health.

In recent years, the analysis of EMG signals has been an interesting topic. A human-machine interface to control exoskeletons that utilizes EMG signals from the muscles of the operator has been presented in [5] along with torque applied and similar parameters. The development of an artificial human arm controlled by muscle Electromyography (EMG) could help to hold the prosthetic hand [6]. This would help disabled people to stay more comfortable.

The people with physical disabilities that have come from diseases such as spinal cord injury, paralysis, and amputation need assistance, which is possible with the use of hand gestures for human-computer interaction (HCI) [7]. Another feasible EMG based HCI [8] for the disabled had been proposed using a RISC-type microprocessor, PIC16F73, and a Bluetooth-based wireless communication system. A detailed study of the research platform for EMG pattern recognition based prosthetic hand is there in [9]. A hand motion estimation using EMG signals with the Support Vector Machine (SVM) algorithm is discussed in [10]. The paper [11] focused on identifying a hand gesture from the EMG signal which was acquired by a sensor-based band.

Time-domain multi-feature extraction and classification of Human hand movements by EMG signals have also been presented in [12]. Motion classification for EMG based Human-robot interface using machine learning is detailed in [13-14]. Another study on detecting the intention of movement of a paralysis patient has been presented in [15] using both EEG signals (from the brain) and EMG signals(from muscles).

3 System Model

Fig. 1 shows the proposed system model which includes recording EMG via electrodes, processing on the EMG signals using EMG SpikerShield, recording and visualizing the EMG signals on the BYB spike recorder app, and extracting features from it before using a Classifier.

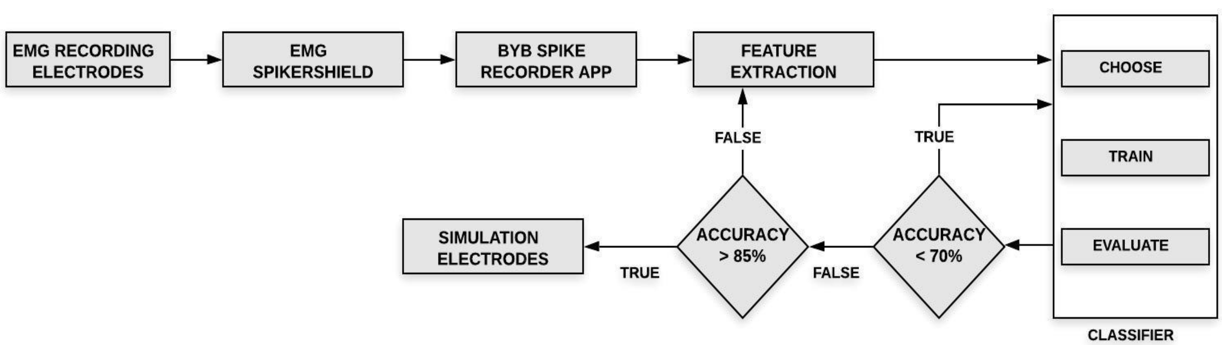


Fig. 1. System design for a human-human interface

3.1 System Architecture

The electrical signal (EMG signal) is a very low-level signal to amplify this signal we will use the EMG Spiker shield circuit. The output of this circuit is given to the analog pins of the Arduino board. This board is programmed to facilitate our desire of controlling the other person. These electrical signals are stored in the EMG SpikerShield. These

EMG signals are displayed on the computer screen using the BYB Spike Recorder App. We can extract features from this app for the dataset. The electrical signals acquired from the controller are communicated to the EMG Spiker shield by connectivity from the electrodes and then these signals are transferred to the controlled using the TENS device. The hardware connections and signal flow in the system are shown in Fig. 2.

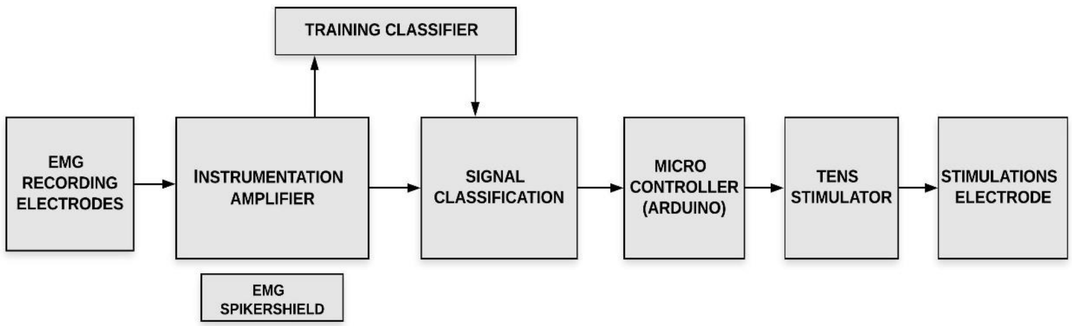


Fig. 2. Connections of Hardware kit for signal flow

The Controller: The Controller is the person whose muscle activity is recorded to control the person with a disability. **The Controlled:** The person who is controlled is hooked up to the all-important TENS stimulation device, which harmlessly delivers electricity to his arm's nerves.

3.2 Data Acquisition Procedure

The electrodes for EMG signal acquisition are placed on the arm of the person and one on the back of the wrist as shown in Fig. 4. The orange muscle electrode cable wire from the EMG Spiker-Shield has then connected to the electrodes on the arm. The measured EMG signals can range from 0V to 30mV peak-to-peak, and the frequencies can be anywhere between 10Hz to 500 Hz depending on the person and how active their muscles are.

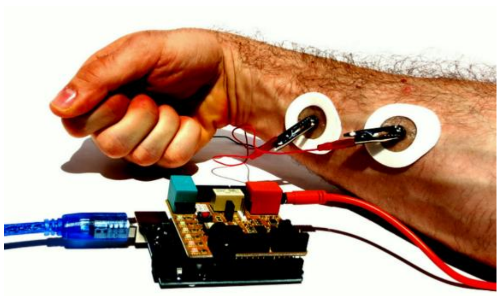


Fig. 4. EMG signal acquisition from an arm of a person (courtesy of backyard brains [16])

3.3 Feature Extraction

Time-domain features are extracted from the recorded EMG signal and the dataset is prepared using these features. This dataset is fed to the algorithms to predict the hand movements of the person. The features extracted are:

1. **Mean Absolute Value (MAV):** It gives the mean of the processed EMG signal.

$$MAV = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (1)$$

2. **Root Mean Square (RMS):** It is the square root of the mean square of the signal.

$$RMS = \sqrt{\frac{\sum_{i=1}^{N} x_i^2}{N}} \quad (2)$$

3. **Standard Deviation (SD):** It shows the deviation of the signal from the mean value.

$$SD = \sqrt{\frac{\sum (x_i - MAV)^2}{N}} \quad (3)$$

4. **Variance (VR):** It shows the deflection of the signal from its mean or absolute value.

$$VR = \frac{\sum (x_i - MAV)^2}{N} \quad (4)$$

5. **Waveform Length (WL):** It is the distance over which a wave's shape repeats**.**

$$WL = \sum_{i=1}^{N} |x_i - x_{i-1}| \quad (5)$$

6. **Zero-Crossing (ZCR):** It is used to count the number of times the EMG signal passes the zero-amplitude axis.

$$ZCR = \frac{1}{T} \sum_{t=1}^{T} |x(t) - x(t-1)| \quad (6)$$

3.4 Classifiers

After feature extraction, the classifiers used for the feature data set obtained are supervised learning models as the training data is labeled. Four classification algorithms namely Decision trees, KNN, SVM, and Naïve Bayes have been used for our feature set.

1. **Decision Tree:** They are used both for classification as well as regression problems. It breaks down a dataset in smaller subsets and the final result is a tree with leaf nodes and decision nodes. The topmost decision node is the best predictor and is called a root node. Decision trees can handle categorical as well as numerical data.
2. **KNN:** The k-nearest neighbor algorithm works based on the nearest neighbors which are found using Euclidean distance. It takes some labeled points and labeling of other points is based on these. While labeling a new point, the labeled points closest to the new point (it's nearest neighbors) are taken care of. The class of the new point is predicted according to the k-nearest neighbors.
3. **SVM:** Support Vector Machine (SVM) is a supervised machine learning algorithm used for both classification and regression tasks. It uses a method called kernel trick to transform the data, based on these transformations it finds optimal boundary between the possible outputs.

4. **Naïve Bayes:** It is an algorithm, which is used for both classification and regression, based on Bayes theorem. It assumes that every feature has an independent contribution to the probability. This classifier is easy to build and useful for very large datasets.

4 Simulation and Results

4.1 Simulation of Circuits on Proteus Software

The EMG signal is given to EMG SpikerShield which will enable to control movements of other persons connected via electrodes. The HHI (human-human interface) of the spiker shield facilitates in controlling the other person. In this circuit, shown in Fig. 5, the instrumentation amplifier, designed using op-amps, is used to amplify low-level signals by rejecting noise. The output of the amplifier is given to the analog pins of the Arduino board. AD623 IC is used, which is an instrumentation amplifier IC, and TLC2274 is IC which exhibits high input impedance and low noise.

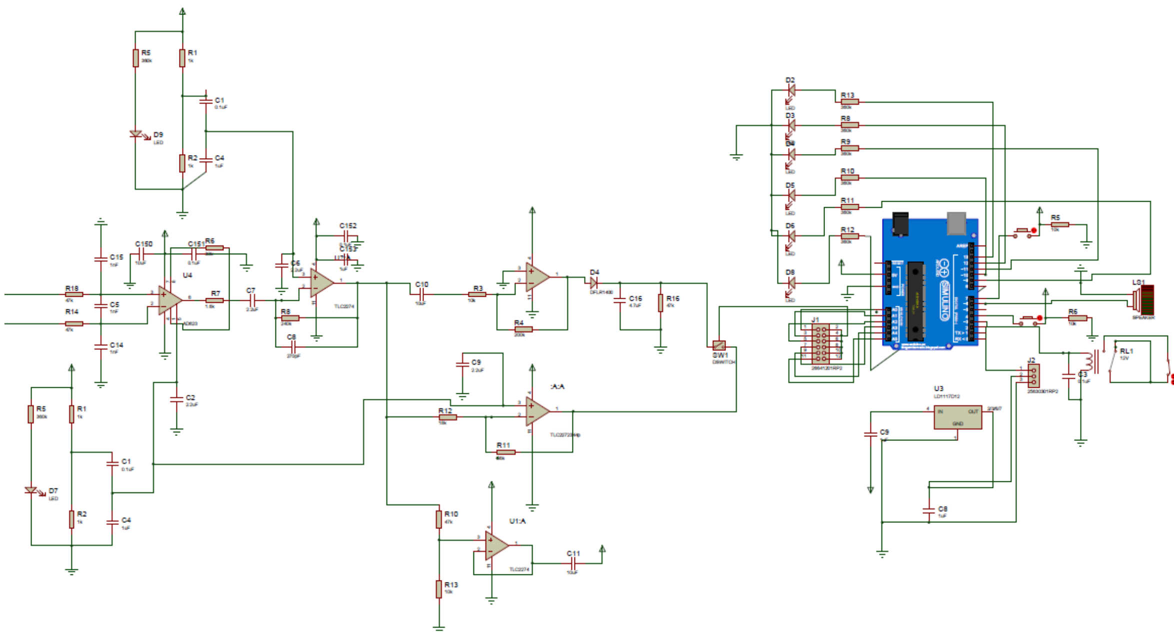


Fig. 5. Proteus circuit of EMG SpikerShield

The circuit of TENS, shown in figure Fig. 6, uses a CMOS 555 timer to produce a brief pulse which feeds a 1:10 miniature transformer. Along with a 4.7nF capacitor, the transformer makes a parallel resonant circuit and the resonance leads to a considerable increase in the output voltage. This circuit delivers enough current to cause muscle contraction and it can modulate pulse width, frequency, and intensity. TENS is applied at high frequency (> 50 Hz) with an intensity that is below motor contraction or at low frequency (< 10 Hz) with an intensity that produces motor contraction. The circuits were converted to .pdf from Proteus and then the image is obtained from .pdf and used here.

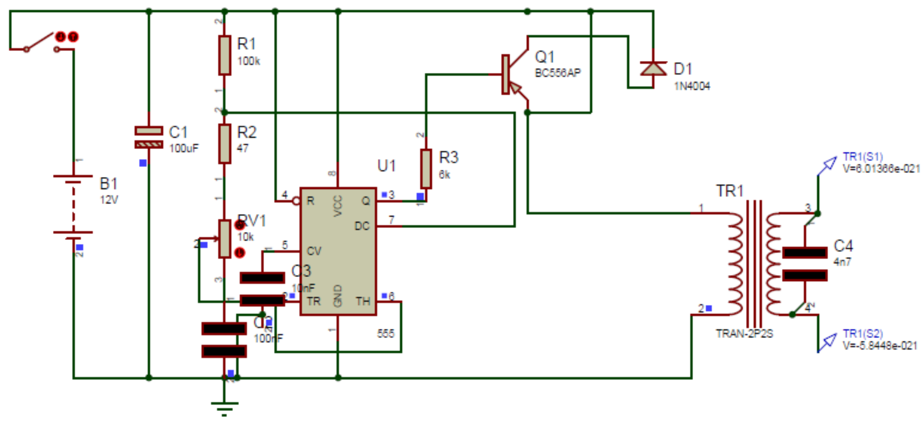


Fig. 6. Proteus Circuit of TENS unit

4.2 Implementation of Machine learning algorithms

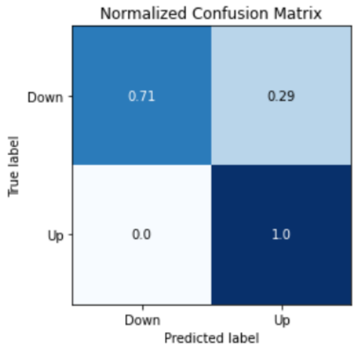
The processed signal obtained from EMG SpikerShield is fit for further processes. The features data set obtained after extracting features from the Spike recorder and mathematical conversions of equations (1-6) using MATLAB is fed to the classification algorithms. The accuracy of 90% for Decision Tree, 60% for KNN, 95% for SVM, and 95% for Naïve Bayes is obtained for the dataset. For KNN the values of k were varied and accuracies for those were checked.

Table 1 shows the training and testing accuracy for all four algorithms.

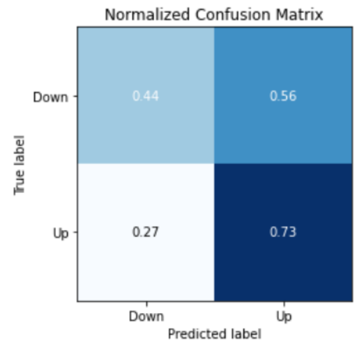
Table 1. Training and Test accuracies of all algorithms

	Training accuracy	**Test accuracy**
Decision Tree	100	90
KNN		
k=2	70	35
k=5	66	60
k=10	66	55
k=20	53	60
SVM	96	95
Naïve Bayes	93.3	95

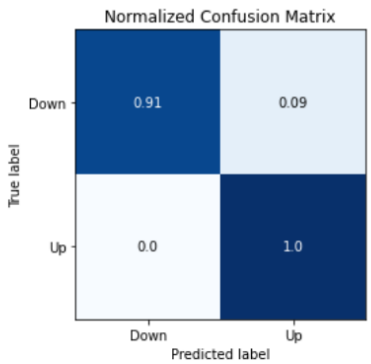
The two hand movements, Up and Down are classified using machine learning algorithms. Confusion matrices are obtained for all the four classifiers. Fig. 7 shows the normalized confusion chart for Decision Tree, KNN, SVM, and Naïve Bayes. The confusion matrix shows the correct classification as well as misclassification. The diagonal elements in the confusion matrix represent the number of true predicted classes and the off-diagonal elements are those corresponding to the misclassified class. The dataset had data of 50 normal people and after splitting using a 60:40 ratio for training and testing, a total of 20 records of people are used in testing, and thus a total of 20 predicted classes are there in the confusion matrix where normalized values have been displayed.



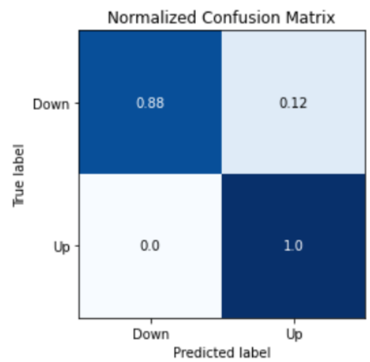
7(a) Normalized confusion matrix for Decision Tree



7(b). Normalized confusion matrix for KNN (k=5)



7(c). Normalized confusion matrix for SVM



7(d). Normalized confusion matrix for Naïve Bayes

Fig. 7. Confusion matrix obtained after applying various machine learning approaches on the dataset

5 Conclusion

In this paper, we presented one of the applications of EMG Signals for the human-to-human interface using feature extraction from EMG signals and then the classification of hand movements using machine learning. We classified the EMG dataset using Decision Tree, KNN, SVM, and Naïve Bayes algorithms and a comparative study has been done. All algorithms gave an accuracy of around 95% except KNN, accuracy for KNN was 60%. This application could be very helpful in providing aid to people with disabilities like Paralysis whose body parts may not be damaged, but their nervous system is not capable of communicating with the muscles. After obtaining data from a normal person, features extracted from the EMG signal will help to control the movements of the disabled person using EMG SpikerShield and a machine learning classifier. Apart from paralysis patients, this procedure could be applied to people suffering from many neuromuscular diseases and unable to move their body parts, especially limbs.

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