CLASSIFICATION ELECTROMYOGRAPHY SENSOR FOR HAND GESTURE RECOGNITION WITH NEURAL NETWORK USING CORRELATION-BASED FEATURE SELECTION

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Abstract- In this paper, we will present a research about hand gesture pattern recognition using electromyography sensors. Data collection process will take 100 samples in time domain data for each gesture, then transformed into frequency domain data and feature extraction to get 18 features. After getting the features, we will perform feature selection with Correlation-based Feature Selection (CFS) to reduce the total features and improve the accuracy of the classification algorithm used, which is the neural network. The analysis process will show the accuracy value of gestures used.

Index Terms- Electromyography Sensor, Feature Selection, Neural Network, Pattern Recognition.

I. INTRODUCTION

Technological advances have embraced all aspects, with technology also we can get data easily. Such as the muscle sensor or electromyography sensor that can record data from changes motion in the muscles, so that data can be filtered and searched information for recognize the hand pattern and also can be applied as sign language.

In the previous research, to detect hand gestures of several approaches such as using computer vision technology [2] i.e. capturing images and processing with image processing technology or using hand-glove approach [3] i.e. creating handmade frames equipped with several types of sensors inside it. The approach with computer vision will depend on the lighting because the data taken is an image. While the hand-glove approach will limit the movement of the hand because the hand has been filled with artificial frameworks hand. Thus, to solve the above problem, a workable solution is to use a surface or bio-acoustic electromotive sensor approach [4], a technique used to record and interpret electrical activity in the hand muscles. The device used is a small sensor that is Electromyography sensor v3, this device will be embedded on the arm so as not to disrupt the movement of the hand itself and also does not require light.

II. CONCEPT & IMPLEMENTATION

This study collects data in time series by using an EMG sensor v3. The position placement of the sensor is maintained constant on certain positions on the right hand. Dataset is collected 100 times for each gesture, and the amount of gesture used in this paper is six gestures as shown in Fig.1.It means we will get 600 data for 6 gestures. After all data have been collected, the data will be separated into two feature generation i.e. time domain data and frequency domain data. Each feature generation will produce 9 features, so we have 18 features input. After all feature sets have been collected, the dataset will be analyzed by using machine learning tools WEKA version 3.8.2. WEKA is a powerful tool for data mining [4], and this tool will also be doing training data process for classification and feature selection process. The analysis process will be implemented on a number of different gestures between 3 gestures to 6 gestures. In addition, collected data will be analyzed with and without feature selection.

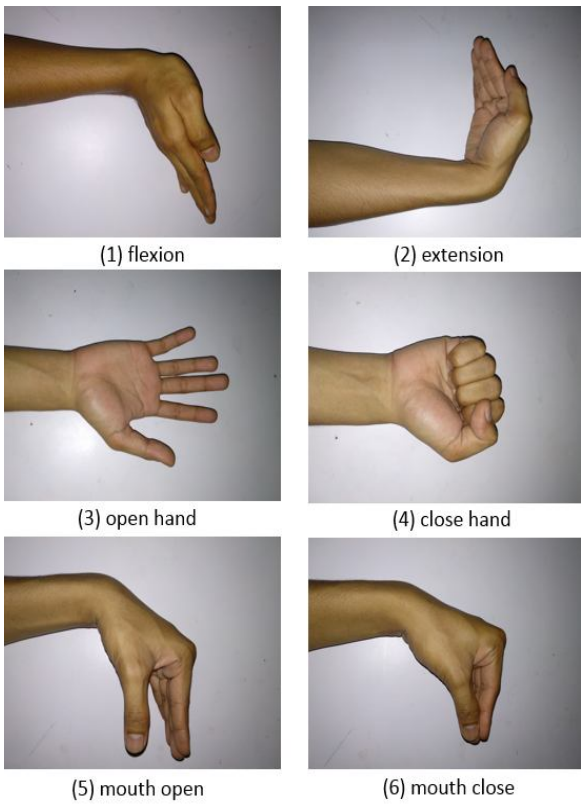


Fig. 1. Gestures used to collect dataset.

III. METHODOLOGY

In this research, we use the pattern recognition process diagram that will start from data up to post-processing as in Fig. 2.

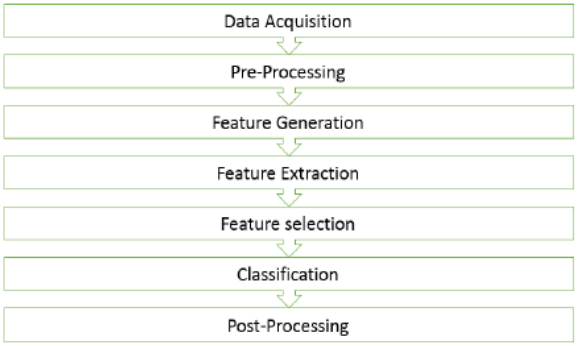


Fig. 2.Pattern recognition process diagram.

A. Data Acquisition

The hardware used is Electromyography sensor v3[1], on this device there are 3 types of inputs that will be mounted on the arm using ECG electrode so that the electrical activity of the muscles can be recorded. The three inputs are mid node, end node, and reference node. Mid and end node used as an electric potential differentiator while reference node used as ground. In the software section will be used Arduino microcontroller as electronic circuit controller. This sensor will run on 9600 baut or 9600 bit/s. On delivery one bytes will contain 10 bits because the output generated on the program is 0-1023.Then, the data transmission process becomes 960 bytes/s. This system will take 100 data with delay time 20ms so that the time needed during data collection in real-time is 2006 ms.

B. Pre-Processing

Pre-processing is an early stage in the process of recording data and useful for eliminating noise and useless data. There are 3 filters data used in this stage where the signal is **amplified**, **rectified** and **smoothed.** These filters allow the data to be processed as not raw EMG data, but instead it has filtered [1]. Amplification is useful to amplify data while the rectification and smoothing wave will change the shape of waveform as a whole.

C. Feature Generation

The feature is an information that represents a data. In this section, there will be two features generation, first generation is **time domain data** and second generation is **frequency domain data**. Time domain data is a form of data directly from the sensor, while frequency domain data is the transformation of data from Time domain data using DFT (Discrete Fourier Transform) [6] as in (1) at the 25Hz frequency sample.

$$x[i]=\sum_{k=0}^{N/2}\mathrm{Re}\,X[k]\cos(2\Pi ki/N)+\sum_{k=0}^{N/2}\mathrm{Re}\,X[k]\sin(2\Pi ki/N) \quad (1)$$

Each feature generation will be taken 9 features, because there are two generation feature it will form 18 features such as (see Table I).

The features used in this paper are combination of some previous research that is [4] and [9] which resulted in 18 features.Because the total is quite many,feature selection is needed so that in addition to reducing computed features, we can alsofindwhich feature has a major influence in the classification.

Table I.Extracted features for each domain.

Time Domain	Frequency Domain
Mean Absolute Value (Mean)	Mean Absolute Value (Mean2)
Maximum amplitude (Max)	Maximum amplitude (Max2)
Minimum amplitude (Min)	Minimum amplitude (Min2)
Waveform Length (WL)	Waveform Length (WL2)
Root Means Square (RMS)	Root Means Square (RMS2)
Standard Deviation (SD)	Standard Deviation (SD2)
Log detector (Log)	Log detector (Log2)
Willison Amplitude (WAMP)	Willison Amplitude (WAMP2)
Slope Sign Change (SSC)	Slope Sign Change (SSC2)

D. Feature Extraction

Feature is an information obtained from a data of set, there are many ways to get that information, as in this data, we can get statistic information from 100 sample data on each gesture.

Mean Absolute Value

The Mean Absolute Value is computed individually for each data (2) i.e. frequency and time domain data.

$$MAV = \frac{1}{N}\sum_{n=1}^{N}|Xn| \quad (2)$$

Maximum amplitude

Maximum amplitude is the highest amplitude value in a sample data (3).

$$Max=\sum_{n=1}^{N} f(Xn, X(n+1)) \rightarrow f(X,Y)=\begin{cases} X, X\geq Y \\ Y, otherwise \end{cases} \quad (3)$$

Minimum amplitude

Maximum amplitude is the lowest amplitude value in a sample data (4).

$$Min=\sum_{n=1}^{N} f(Xn, X(n+1)) \rightarrow f(X,Y)=\begin{cases} X, X\leq Y \\ Y, otherwise \end{cases} \quad (4)$$

Waveform Length

Waveform Lengthis the distance value between each data in each sampledata (5).

$$WL = \sum_{n=1}^{N}|X(n+1)-Xn| \quad (5)$$

Root Means Square

The Root Mean Square directly reflects the amount of muscleactivity (6).

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} Xn^2} \qquad (6)$$

Standard Deviation

Standard Deviation is value to find the threshold level of muscle contraction activity (7).

$$SD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(Xn - MAV)^2} \qquad (7)$$

Log detector

$$Log = e^{\sqrt{\frac{1}{N}\sum_{n=1}^{N}\log|Xn|}} \qquad (8)$$

Willison Amplitude

Willison Amplitude counts the number of times the difference between two subsequent values exceeds a certain threshold (9). The threshold to 30% of the maximum EMG value.

$$WAMP = \sum_{n=1}^{N} f(|X(n+1) - Xn|)$$
$$f(X) = \begin{cases} 1, X \geq threshold \\ 0, otherwise \end{cases} \qquad (9)$$

Slope Sign Change

The number of changes between positive and negative slope (10) among three consecutive segments are performed with the threshold function for avoiding the interference EMG signal.

$$WAMP = \sum_{n=2}^{N} f[(Xn - X(n-1)) \times (Xn - X(n+1))]$$
$$f(X) = \begin{cases} 1, X \geq threshold \\ 0, otherwise \end{cases}$$

(10)

E. Feature Selection

This paper uses the approach of Correlation-based Feature Selection (CFS)for feature selectionas illustrated in Fig. 3.

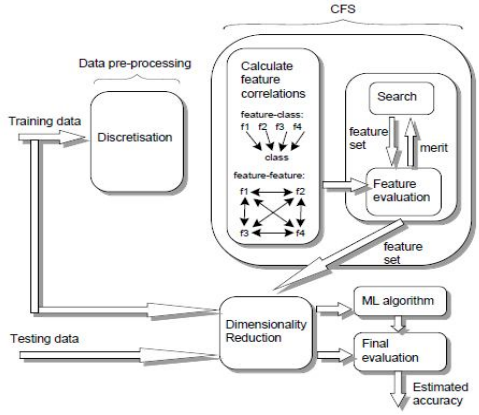


Fig. 3.Correlation-based Feature Selectionmethod [7].

In Fig.3 will calculate **relief** [8] in (11) to find correlation between two features using instance based learning to assign weight to each feature with class or with other features.

$$RELIEF = Wx - \frac{diff(X,R,H)^2}{m} + \frac{diff(X,R,M)^2}{m} \qquad (11)$$

Where, W_x represents the weight for attribute *x*.*R* represents a randomly sampled instance. represents the nearest hit. *M* represents the nearest miss.*m*represents the number of randomly sampled instances. The function *diff* calculates the difference between two instances for a given attribute. For nominal attributes, it is defined as either 1 (the values are different) or 0 (the values are the same).

Next, the data will be divided into several subsets of data until the subset reaches 2^n (number of features), then searches the value of **merit** or M_s[7] with function (12) on each subset formed, so we can see the best subset feature by looking at the merit point. As (Table II) is subset selected because it has highest merit point of the other subset.

$$Ms = \frac{k\overline{rcf}}{\sqrt{k + k(k-1)\overline{rff}}} \qquad (12)$$

Where, $M_s$represents the heuristic merit of a feature subset *S* containing *k* features. Then,*rcf*represents the mean feature-class correlation and *rff*represents the average feature-feature inter correlation.

Table II.Merit points of feature selection.

Total Gesture	Reduction	Merit Point
3	77.78%	0.983
4	72.22%	0.807
5	16.67%	0.807
6	44.44%	0.734

Table III.Selected features on each gesture group.

Total Gesture	Total Selection	Information
3	4	Mean, WAMP, Min2, WAMP2
4	5	Max, WL, Min2, Mean2, RMS2
5	15	Max, Min, WL, Mean, RMS, SD, WAMP, SSC, Min2, WL2, Mean2, RMS2, Var2, SSC2, Log2
6	10	Max, WL, Mean, SD, WAMP, SSC, Min2, WL2, Mean2, Var2

Table III is the result of feature selection performed on different dataset of gesture numbers. There are several features that often appear such as “Mean”, “Mean2”, “WAMP”, “Min2”, “Max”, and “WL” which appeared for 3 times. So this shows the strength of that features.

F. Classification and Training Data

The classification algorithm we use is the neural network. Input section there will be 18 input data features that will be selected into several inputs, the

output will be divided into 6 gestures according in (Fig. 3). The training data will use 10-fold cross-validation for test mode.

Next will be shown classification results with comparing use of CFS and without use of CFS.

Table IV.Classification Neural Network

Total Gesture	TP Rate	FP Rate	Precision	Recall	F Measure	MCC	ROC Area	PRC Area	Class
3	0.980	0.000	1.000	0.980	0.990	0.985	1.000	0.999	1
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	2
	1.000	0.010	0.980	1.000	0.990	0.985	1.000	0.999	3
	0.993	0.003	0.993	0.993	0.993	0.990	1.000	0.999	Avg.
4	0.920	0.027	0.920	0.920	0.920	0.893	0.990	0.978	1
	1.000	0.003	0.990	1.000	0.995	0.993	1.000	1.000	2
	0.880	0.043	0.871	0.880	0.876	0.834	0.981	0.939	3
	0.830	0.050	0.847	0.830	0.838	0.785	0.969	0.916	4
	0.908	0.031	0.907	0.908	0.907	0.876	0.985	0.958	Avg.
5	0.970	0.013	0.951	0.970	0.960	0.999	0.950	0.996	1
	0.940	0.015	0.940	0.940	0.940	0.925	0.993	0.980	2
	0.850	0.035	0.859	0.850	0.854	0.818	0.984	0.929	3
	0.880	0.020	0.917	0.880	0.898	0.873	0.983	0.896	4
	0.820	0.053	0.796	0.820	0.808	0.759	0.963	0.909	5
	0.892	0.027	0.892	0.892	0.892	0.865	0.984	0.942	Avg.
6	0.920	0.008	0.958	0.920	0.939	0.927	0.993	0.970	1
	0.930	0.016	0.921	0.930	0.925	0.910	0.992	0.957	2
	0.890	0.034	0.840	0.890	0.864	0.836	0.979	0.928	3
	0.900	0.032	0.849	0.900	0.874	0.848	0.983	0.891	4
	0.760	0.038	0.800	0.760	0.779	0.737	0.966	0.878	5
	0.780	0.036	0.813	0.780	0.796	0.756	0.946	0.863	6
	0.863	0.027	0.863	0.863	0.863	0.836	0.976	0.914	Avg.

Table. V Classification neural network with CFS.

Total Gesture	TP Rate	FP Rate	Precision	Recall	F Measure	MCC	ROC Area	PRC Area	Class
3	0.990	0.005	0.990	0.990	0.990	0.985	0.999	0.998	1
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	2
	0.990	0.005	0.990	0.990	0.990	0.985	0.997	0.989	3
	0.993	0.003	0.993	0.993	0.993	0.990	0.999	0.996	Avg.
4	0.940	0.020	0.940	0.940	0.940	0.989	0.920	0.978	1
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	2
	0.920	0.053	0.852	0.920	0.885	0.845	0.980	0.929	3
	0.800	0.040	0.870	0.800	0.833	0.782	0.963	0.919	4
	0.915	0.028	0.915	0.915	0.914	0.887	0.983	0.956	Avg.
5	0.980	0.005	0.980	0.980	0.980	0.975	0.997	0.993	1
	0.940	0.015	0.940	0.940	0.940	0.925	0.993	0.980	2
	0.880	0.025	0.898	0.880	0.889	0.862	0.989	0.954	3
	0.890	0.020	0.918	0.890	0.904	0.880	0.985	0.908	4
	0.870	0.045	0.829	0.870	0.849	0.810	0.970	0.914	5
	0.912	0.022	0.913	0.912	0.912	0.890	0.987	0.950	Avg.
6	0.920	0.010	0.948	0.920	0.934	0.921	0.993	0.969	1
	0.890	0.016	0.918	0.890	0.904	0.885	0.993	0.960	2
	0.920	0.032	0.852	0.920	0.885	0.861	0.986	0.923	3
	0.900	0.030	0.857	0.900	0.878	0.853	0.984	0.905	4
	0.810	0.034	0.827	0.810	0.818	0.782	0.973	0.910	5
	0.800	0.030	0.842	0.800	0.821	0.786	0.944	0.879	6
	0.873	0.025	0.874	0.873	0.873	0.848	0.979	0.924	Avg.

The (see Table IV) is a gesture classification with neural network using 18 (see table I) or without using feature selection. Whereas, (see Table V) is the result of NN classification whose features have been reduced by using CFS feature selection as in (see Table IV).

G. Post-Processing

To evaluate the ability of one muscle sensor, we compare the use of gestures from 3 to 6 gestures as Fig. 4. The best accuracy for gesture classification is the use of 3 gestures because it has an accuracy of 99.33%. The more gestures used, the more it will go down. for the use of CFS is effective because 3 of 4 patterns of data accuracy, all experienced an increase of up to 3% and from a significant feature use reduction of 77.78% or from 18 features in the select into 4 features to be used.

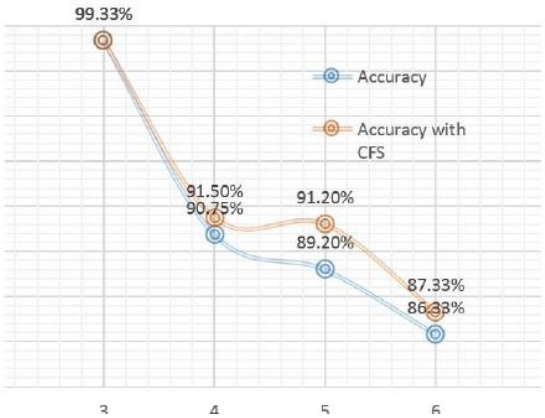


Fig. 4. Accuracy comparison.

CONCLUSION

According to the result of feature selection (see Table III), there are 6 features that appear 3 times of 4 experiments. This indicates feature has a great influence in the classification result.

According to comparison shown in Fig. 4, it can be concluded that the use of CFS for feature selection successfully improved data accuracy and reduced the use of features for machine learning algorithm. It is also found that one muscle sensor is effective inclassifying 3 gestures. However according to experimentation, one muscle sensor in classifying 4 gestures was limited to only certain types of gestures because there are some gestures that look the same but different.

For subsequent research and developments, it is possible to create more real-time tools supported by the above data as well as the above methods can also be developed by increasing the number of sensors so that the resulting gesture will become more and more accurate.

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