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# Pattern Recognition of Facial Electromyography (FEMG) Signal for Aceh Language Speech using Naïve Bayes and Learning Vector Quantization (LVQ)

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# Pattern Recognition of Facial Electromyography (FEMG) Signal for Aceh Language Speech using Naïve Bayes and Learning Vector Quantization (LVQ)

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**Abstract**. Facial electromyography is myoelectric signals that formed by human facial muscles. This signal can be acquired by attaching an electrode to the facial muscle that has been connected with an electromyography sensor. When human say certain words, the articulation muscles contract and facial electromyography signals appear in the muscles. This study aims to recognize patterns in facial electromyography signals by classifying signals using naïve bayes and learning vector quantization classifier. Feature extraction used one-dimensional discrete wavelet transforms. Wavelet transform type used wavelet daubechies2 level 5. The transformation produces a level 5 approximation coefficient called a5 and five detail coefficients called d1, d2, d3, d4, and d5. The result of this study show that the average classification accuracy for *ho neuk jak* sentence using naïve bayes and LVQ classifier was 62.5% and 92.5% respectively. The average classification accuracy for *ja'* word using naïve bayes and LVQ classifier was 70% and 92.5% respectively. The average classification accuracy for *ja' wo* sentence using naïve bayes and LVQ classifier was 52.5% and 90% respectively. The average classification accuracy for *pane* word using naïve bayes and LVQ was 70% and 90% respectively. The average classification accuracy for *soe* word using naïve bayes and LVQ classifier is 85% and 95% respectively. Thus, this study shows that when humans say the words, facial electromyography signals that appear on facial muscles difference for each subject.

Keyword: Pattern Recognition, Facial Electromyography, Aceh Language Speech, Naïve Bayes, Learning Vector Quantization

## 1. Introduction

The development of science and technology has influenced human's life, especially in the field of pattern recognition. Human have electromyography (FEMG) signal that occurs due to muscle contraction. In addition to the signals that appear in the muscles of the arms and lower body, the human also have electromyography signals in the face. Signals that appear on the face are called facial electromyography (FEMG) signal.

Facial electromyography is usually used to measure the expression of emotions on human faces. This FEMG signal is recorded by attaching an electrode to facial skin. This expression of emotion is usually an expression of pleasure, sadness, and anger. The facial muscles commonly used to measure this expression are corrugators supercili, zygomaticus major and orbicularis oculi [1,2]. This emotion expression can be interpreted with the magnitude of facial electromyography signal

FEMG signals can also be used to recognize the human facial gestures for assistive and rehabilitation technology [3-4]. In addition, to measure emotional expressions and facial gestures, FEMG signals can also be used to distinguish speech in communicating through the signal patterns. When humans do speech-language, the articulation muscles around the mouth contraction that causes FEMG signals. FEMG signals that appear in certain muscles analysed specifically for being used in human speech patterns recognition. The difference in language speech was indicated by differences in FEMG signal patterns. Thus FEMG signal pattern can be used as a unique identity. In addition, this FEMG signal can also be used as a medium to convey information in understanding the language conveyed to deaf people.

## 2. Related Studies

Speech recognition based on facial electromyography (FEMG) signals has been carried out by several researchers. Research conducted by [5] about silent speech interfaces on the introduction of Spanish syllables based on EMG signals that are on facial muscle. The syllables used are vowels, labials, dentals, palatals, velars, and alveolar. The validation method used 10 fold cross-validations. The results showed that average 70% of the 30 syllables could be recognized. The next research conducted by [6] about the introduction of Thai language for classifying five tones based on electromyography signals recorded from six electrode positions placed on the face and neck muscles when the participant is speaking 21 words of Thai with five tones for each word. Artificial neural networks were used to classify the EMG signals. The feature of EMG signal was a signal that has the 5 highest values from the RES index. The results show that the accuracy was 56.2% for classifying five Thai tones. The next research conducted by [7] about the introduction of vowels in the spelling of the 11 letters of Bangli. The EMG signal feature selection uses the minimum Redundancy Maximum Relevance (mRMR) method and the signal classification uses an artificial neural network (ANN). The results show that the accuracy value was 82.3%. The next research conducted by [8] about how speech synthesis techniques were directly derived from surface electromyography signals in facial articulation muscles. Four methods of capturing the features used are gaussian mixture model (GMM), deep neural network (DNN), long short term memory (LSTM) and unit selection. Among the four methods discussed, the DNN method has shown the best performance.

In this study, researcher conducted a classification of facial electromyography signals in Acehnese speech using two classifiers, namely naïve bayes and learning vector quantization. The feature extraction method used wavelet transform type daubechies2 level 5 by calculating the mean for the approximation coefficient (a5) and the detail coefficient (d1-d5).

## 3. Methodology

The method used in this study is carried out in several stages. There are FEMG signal acquisition, FEMG signal extraction using wavelet transform and classification using naïve bayes and learning vector quantization (LVQ).

### *3.1. Research Flowchart*

Research flowchart of this study is shown in Figure 1.

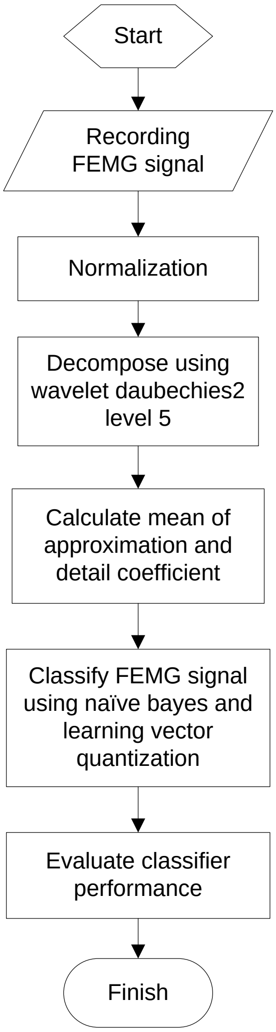


**Figure 1.** Research flowchart.

### *3.2. Data Acquisition*

The data acquisition by using several devices namely surface electrode, FEMG sensor, and arduino uno. Surface electrode and FEMG sensor are shown in Figure 2. The FEMG signal can be obtained by attaching a surface electrode to masseter, risorius and depressor muscles. The reference electrode is attached to the masseter muscle. The electrode placement point of FEMG is shown in Figure 3.

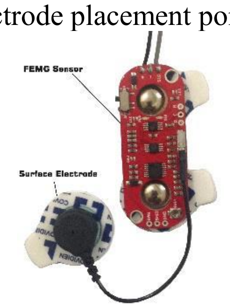


**Figure 2.** The FEMG sensor and surface electrode.

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**Figure 3.** The electrode placement point.

The FEMG signal recording uses CoolTerm software. Every word spoken will be standardized by giving initialization time at the beginning and termination time in the end. This initialization and termination time is needed to ensure the normal conditions. The initialization and termination time is 5 seconds.

The number of subjects involved in this study was 4 native Acehnese speakers. They said as many as 5 words as shown in Table 1. Each subject was taken for 10 times of the pronunciation of the word.

**Table 1.** English and Aceh Language Vocabulary.

| No. | English | Aceh |
|---|---|---|
| 1. | Where | Ho neuk jak |
| 2. | Go | Ja’ |
| 3. | Go home | Ja’ wo |
| 4. | Come from | Pane |
| 5. | Who | Soe |

### *3.3. Data Extraction*

The FEMG signal was normalized using zero mean and extracted using wavelet transforms. An overview of the wavelet transform decomposition process is shown in Figure 4.

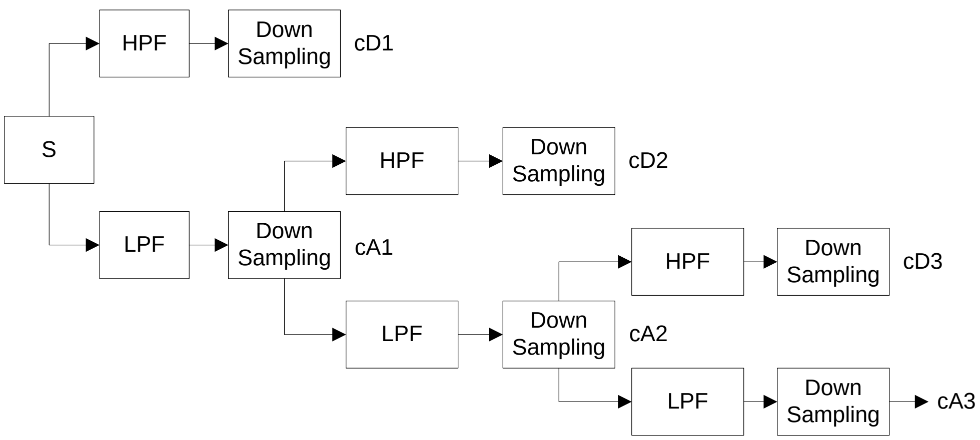


**Figure 4.** An overview of wavelet transform decomposition for FEMG signal.

Figure 4 above shows that the wavelet transformation decomposition uses two filters, low pass filter and high pass filter. The low pass filter decomposes the signal to produce approximation components and the high pass filter decomposes the signal to produce detailed components. In this

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study, the wavelet transform used daubechies2 level 5. It means that it produces an approximation component (a5) and detail components (d1 – d5).

Mean value was calculated for each approximation and detail component so that the signal feature for classifying is six units. The LVQ network simulation uses weka opensource software. The method for training and testing data in LVQ dan naïve bayes classifier uses 5 – cross validation. Learning rate is 0.1 and iteration is 10.

## 4. Result and Discussion

The features of EMG signal were trained and tested using naïve bayes and learning vector quantization. The result of training and testing data can be obtained as shown in Table 2. The accuracy of the value can be calculated from true positive, true negative, false positive and false negative obtained [9].

**Table 2.** The accuracy of FEMG signal classification.

| No. | Vocabulary | Classifier | Subject | Accuracy (%) |
|---|---|---|---|---|
| 1. | Ho neuk jak | Naïve bayes | #1 | 90 |
| | | | #2 | 70 |
| | | | #3 | 30 |
| | | | #4 | 60 |
| | | LVQ | #1 | 100 |
| | | | #2 | 80 |
| | | | #3 | 90 |
| | | | #4 | 100 |
| 2. | Ja’ | Naïve bayes | #1 | 80 |
| | | | #2 | 30 |
| | | | #3 | 90 |
| | | | #4 | 80 |
| | | LVQ | #1 | 100 |
| | | | #2 | 100 |
| | | | #3 | 70 |
| | | | #4 | 100 |
| 3. | Ja’ wo | Naïve bayes | #1 | 30 |
| | | | #2 | 100 |
| | | | #3 | 60 |
| | | | #4 | 20 |
| | | LVQ | #1 | 100 |
| | | | #2 | 100 |
| | | | #3 | 70 |
| | | | #4 | 90 |
| 4. | Pane | Naïve bayes | #1 | 80 |
| | | | #2 | 90 |
| | | | #3 | 90 |
| | | | #4 | 20 |
| | | LVQ | #1 | 100 |
| | | | #2 | 100 |
| | | | #3 | 70 |
| | | | #4 | 90 |
| 5. | Soe | Naïve bayes | #1 | 80 |
| | | | #2 | 100 |
| | | | #3 | 80 |

| | | |
|---|---|---|
| | #4 | 80 |
| LVQ | #1 | 100 |
| | #2 | 100 |
| | #3 | 80 |
| | #4 | 100 |

Table 2 shows that every word pronounced by each subject has a different classification accuracy. For the pronunciation of the word *ho neuk jak*, LVQ classifier has better accuracy than naïve bayes classifier with the greatest classification accuracy in the amount of 100% for subject#1 and subject#4. For the pronunciation of the word *ja '*, LVQ classifier has better accuracy than naïve bayes classifier with the greatest classification accuracy in the amount of 100% for subject#1, subject#2 and subject#4. For the pronunciation of the word *ja' wo*, LVQ classifier has better accuracy than naïve bayes classifier with the greatest classification accuracy in the amount of 100% for subject#1 and subject#2. For the pronunciation of the word *pane*, the LVQ classifier has better accuracy than the naïve bayes classifier with the greatest classification accuracy in the amount of 100% for subject#1 and subject#2. And for the pronunciation of the word *soe*, the LVQ classifier has better accuracy than the naïve bayes classifier with the greatest classification accuracy in the amount of 100% for subject#1, subject#2 and subject#4.

In general, the description of the classification accuracy for each word pronunciation for naïve bayes classifier is shown in Figure 5 while the classification accuracy for each word pronunciation for learning vector quantization classifier is shown in Figure 6

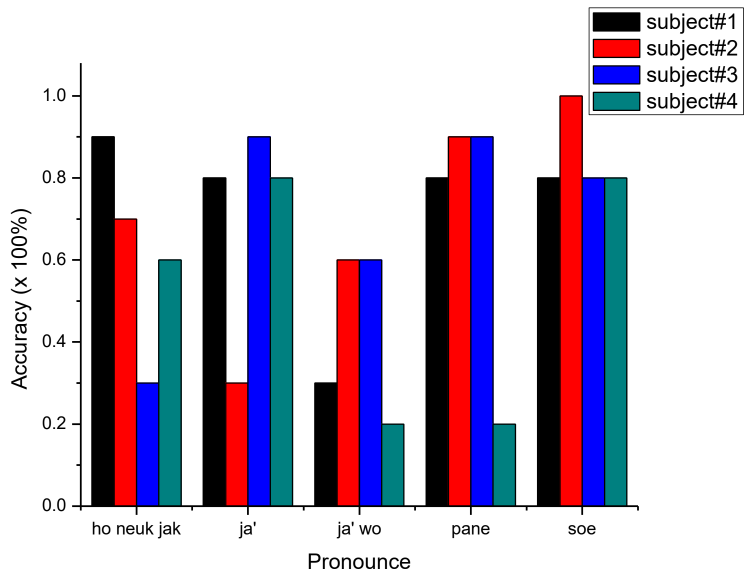


**Figure 5.** Accuracy of FEMG signal classification for naïve bayes classifier.

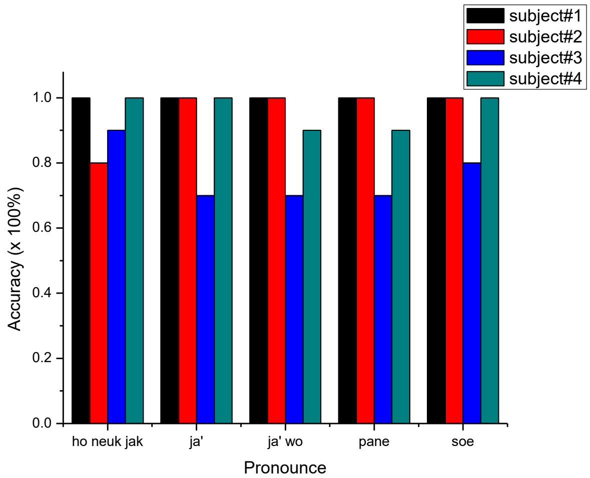


**Figure 6.** Accuracy of FEMG signal classification for LVQ classifier.

Figure 5 explains that subject#2 has only the greatest classification accuracy using naïve bayes classifier for pronouncing the word *soe* by 100%. While Figure 6 explains that subject#1 and subject#4 have classification accuracy using LVQ classifier for pronouncing the word *ho neuk jak* by 100%. Subject#1, subject#2 and subject#4 have classification accuracy for pronouncing the word *ja'* by 100%. Subject#1 and subject#2 have classification accuracy for pronouncing the word *ja' wo* by 100%. Subject#1 and subject#2 have classification accuracy for pronouncing the word *pane* by 100%. Subject#1, subject#2 and subject#4 have classification accuracy for pronouncing the word *soe* by 100%. The classification accuracy of 100% explains that all tested FEMG signals are very well recognized. This indicates that the FEMG signal has a different pattern between one subject and another so that this FEMG signal can be used as a unique identity for every human.

The ROC area value for each subject is shown in Figure 7. The maximum ROC value is 1. There is only 1 subject that has an ROC value below 0.7, naive bayes classifier for subject#3 (*ho neuk jak* and *ja' wo*). In this study, the performance of the classifier was found to be very good for classifying the FEMG signal.

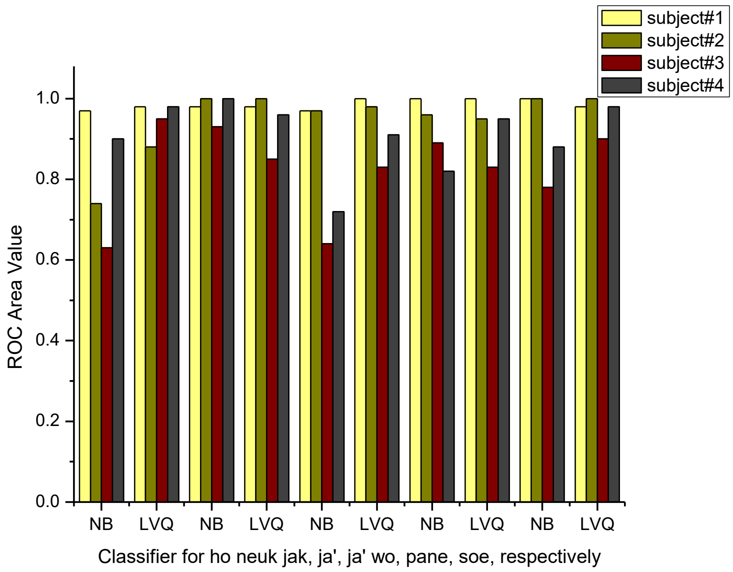


**Figure 7.** ROC area for naïve bayes and LVQ classifier performance.

## 5. Conclusions

The results of the study also suggest that the facial electromyography signal in facial muscle can be used to identify speech recognition. The best facial electromyography signal classification accuracy is LVQ classifier. The classification accuracy for *ho neuk jak*, *ja'*, *ja' wo*, *pane* and *soe* are 92.5%, 92.5%, 90%, 90% and 95% respectively. In this study has also shown that the feature selection and classifier method was sophisticated for studying the FEMG signal pattern recognition. Further research might investigate the FEMG signal classification involving more participants so that the classification can achieve better accuracy.

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