Comparison of Different Time-domain Feature Extraction Methods on Facial Gestures' EMGs

M. Hamedi, Sh-H. Salleh, A. M. Noor, T. T. Swee, and I. K. Afizam
Center for Biomedical Engineering, Transportation Research Alliance
Universiti Teknologi Malaysia, Skudai, Malaysia

Abstract— Electromyography is a bio-signal which is applied in various fields of study such as motor control, neuromuscular physiology, movement disorders, postural control, human machine/robot interaction and so on. Processing of these bio-signals is the essential fact during each application and there still can be seen many challenges among researchers in this area. This paper is focused on the comparison between the classification performances by using different well known feature extraction methods on facial EMGs. Totally ten facial gestures namely smiling with both side of lips, smiling with left side of lips, smiling with right side of lips, opening the mouth like saying 'a' in apple word, clenching the molar teeth, gesturing 'notch' by raising the eyebrows, frowning, closing the both eyes, closing the right eye and closing the left eye are recorded from 6 participants through 3 bi-polar recording channels. In the first step, the signals are filtered to get prepared for better processing. Then, time-domain feature extraction methods INT, MAV, MAVS, RMS, VAR, and WL are applied to signals. Finally, the features are classified by Fuzzy C-Means in order to achieve the recognition accuracy and evaluate the performance of each feature extraction method. This work is carried out by revealing that, RMS gives the most probability amplitude approximation in a steady power and non-tiring contraction when the signal is modeled as Gaussian random process. In contrary, WL proved its weakness in estimating the value of facial EMGs.

1. INTRODUCTION

Gestures recognition is the state-of-the-art which can be added and applied in various fields of research [1]. Gestures usually originate from the face and body. This technology has been done by capturing the images or videos from the body movements or recording the Electromyogram (EMG) of muscles neural activities. Recently, many researchers have been interested in the second method because of observed drawbacks in image-based method. Besides, among all body movements, facial gestures and expressions are focused in different applications especially in the field of human computer interaction (HCI). As examples: facial gestures extracted during speech and transformed as control commands by Arjunan and Kumar [2]; a later proposition of controlling a hands-free wheelchair through the facial myosignals by Firoozabadi et al. [3]; application of five facial gestures by Rezazadeh et al. [4] for designing and controlling a virtual crane training system. Obviously, the most important step in these works is data analysis which many challenges still can be seen.

The main source of data is EMG from the target muscles which are the measurement of their electrical activity. There are two ways to record the EMG which are the invasive by using needle electrodes and noninvasive by applying the surface electrodes. Depending on recording method, the EMG analysis can be varying. Due to surface Electromyography characteristics, this method has been more considered in recent works like stated examples.The amplitude of surface EMG (SEMG) signal is random and the range is 0–10 mV and the frequency range is restricted to the 10 to 500 Hz that both are different in each muscle. So, depending on the muscle under investigation the methods for EMG analysis are diverse. Facial muscles which are considered as a new communication channel with computers and machines in HCI systems produce signal with lower amplitude and almost similar frequency range, Hamedi et al. [5].

Raw recorded EMG signals are quasi random and has complicated form. They also contain significance information as well as contamination and workings with them have been always a tough task. Therefore, EMGs need to be analysis preprocessing, processing and postprocessing of signals can be seen as the three main steps. One of the most important and challengeable part in EMG processing is feature extraction which usually apply on raw signals in order to transform it into reduced representation set of features. There are three types of features in different domain; Time, Frequency and Time-Frequency distribution which each of these categories use in specific application. According to facial EMGs specifications, their accurate and useful features are limited in Time-domain.

Mean Absolut Value (MAV), Maximum Scatter Difference (MSD), Root Mean Square (RMS), Power Spectrum Density (PSD), Absolute Value (AV), Mean Absolute Deviation (MAD), Standard Deviation (SD) and Variance (VAR) are the most popular and well-known methods which have been used by Moon et al. [6], Firoozabadi et al. [3], Ang et al. [7], Gibert et al. [8], Rezazadeh et al. [4], Van den Broek et al. [9] and Hamedi et al. [5, 10]. After feature extraction, they used various techniques of classification for recognition between their chosen facial gestures to prepare them in their own applications such as Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), K-Nearest Neighbors (K-NN) and Fuzzy C-Means (FCM). In these works the number of classes are varies from two to eight and different facial gestures were considered. Hamedi et al. [5] provided the maximum number of classes (eight) and achieved 91.8% recognition by applying RMS and FCM methods for feature extraction and classification respectively.

In this paper, the evaluation between six famous feature extraction methods: Integrated (INT), MAV, Mean Absolute Value Slop (MAVS), RMS, VAR, and Wave Length (WL) on ten facial gestures is described. The goal is the comparison of their performances while FCM classifier used for classification and recognition.

2. METHODOLOGY

The general block diagram of the whole procedure is shown in Figure 1. At first, all six subjects (all healthy male within the range of 20–26 age) get prepared for EMG recording. It was done by cleaning the subjects face from any dust and sweat with using alcohol pad. Then, conductive electrode paste is applied in order to reduce the artifacts as much as possible. In this work three pairs of surface electrodes are used and they positioned in bipolar configuration on the affective muscles involved in chosen gestures. In this study ten predefined gestures: smiling with both side of lips, smiling with left side of lips, smiling with right side of lips, opening the mouth like saying 'a' in apple word, clenching the molar teeth, gesturing 'notch' by raising the eyebrows, frowning, closing the both eyes, closing the right eye and closing the left eye are selected. So, to cover the main muscles in these gestures one pair of the electrodes placed on the Frontalis muscle (Channel 2), two pairs are located on left and right side of temporalis muscles (channel 1&3) and another electrode is situated on the left wrist.

Before signal recording all subjects trained how to perform all ten gestures and then, they rested for 1 minute. After that, they were asked to execute all facial gestures 5 times, as 2 secs performance and 8 secs interval rest between each trial.

2.1. Conditioning of Raw EMGs

All acquired signals were passed through a band-pass filter within the frequency range 30–450 Hz, being the principal frequency range of EMG signals. In addition, in order to avoid from any undesirable artifacts which mostly have low frequency like eye movements, a high-pass filtering at 20 Hz is applied. Moreover, by using a notch filter 50 Hz, power line interferences are removed, Van Boxtel [11].

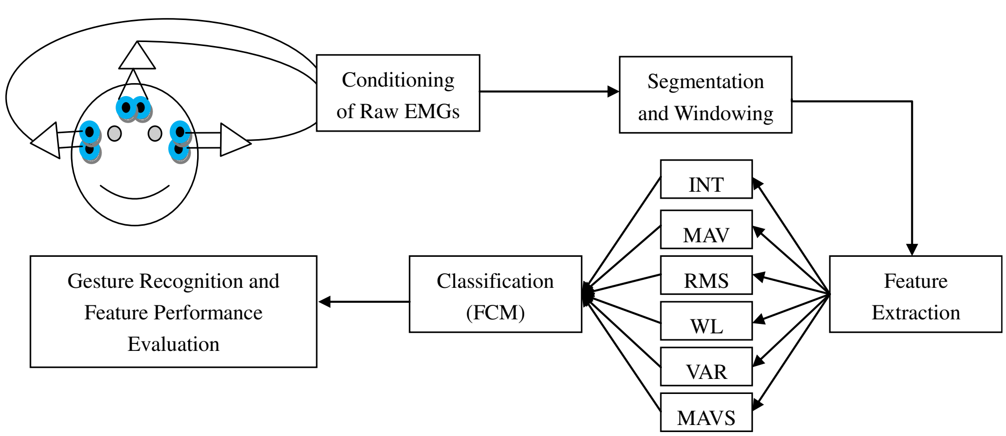


Figure 1: General block diagram of the whole procedure.

2.2. Segmentation and Windowing

In this work all filtered signals are segmented with 256 ms length and the steady-state part of the data were under investigation. Besides, adjacent windowing method is considered prior to feature extraction.

2.3. Feature Extraction

Using entire EMGs as input data for pattern recognition and classification step is not practical because of huge number of data and longtime of processing. So, feature extraction methods have been used to map the real signals into lower dimension feature vectors. The features must contain enough information of signals and must be simple enough for fast training and classification. There have been many experiments in choosing the best method of feature extraction use for facial EMG signals. In this work, six methods INT, MAV, MAVS, RMS, VAR, and WL are chosen to apply on all signals which are explained by Rechy-Ramirez and Hu [12].

2.4. Classification

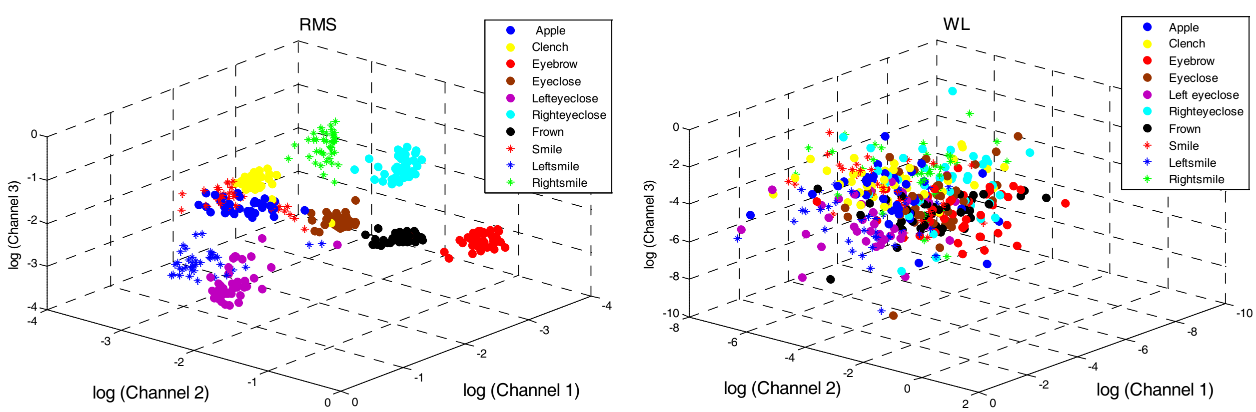
There are many techniques introduced and proposed in the field of facial EMG signals classification such as Multi-Layer Perceptron (MPL), Fuzzy C-Means (FCM) and Support Vector Machine (SVM). It can be observed that, fuzzy clustering classifiers like FCM performed better in compare with other methods due to its flexibility, fast training, easy to use and low cost of calculation. Besides, the supervised version of FCM led to better classification because of class labels which always provide expedient directions during the training procedure. So, FCM classifier used on all extracted features in order to achieve the discrimination and recognition ratios to find the best feature among proposed methods.

3. RESULTS AND DISCUSSIONS

The main goal of this paper was to find better feature extracted from facial EMGs between INT, MAV, MAVS, RMS, VAR, and WL. Table 1 provided the average classification results of ten facial gestures from all participants of all features. As can be seen RMS and WL features delivered the highest and lowest recognition accuracy amongst all features respectively. Figure 2 demonstrates how the RMS and WL features are distributed in feature space. Obviously, all ten clusters are formed for RMS features and except of two classes Apple and Smile which are overlapped too much, the other classes are discriminated well enough. On the other hand, WL features shown their weaknesses for EMG classification. This is due to the fact that, the WL values for all facial gestures are almost close to each other and there is no way to discriminated them. INT, MAV and MAVS features also provided good distribution with almost similar recognition accuracy results in compare with VAR.

Table 1: Average classification results of all features.

Feature	INT	MAV	MAVS	VAR	RMS	WL
Classification Result	87.5%	84.6%	89.7%	35.7%	90.8%	21.5%



(a) (b)

Figure 2: Distribution of RMS and WL features in feature space.

4. CONCLUSIONS

This study highlights an evaluation between six kinds of Time-Domain features which all of them have been already used in various works where EMG signals were involved. Ten facial gestures EMG signals have been recorded form six participants and all considered features were extracted. Then, they were classified by FCM and evaluated by their recognition performances. RMS features shown their abilities in facial gestures EMGs processing and it proved that when a signal is modeled as a Gussian random process, RMS provides the maximum likelihood estimation of amplitude in a constant force and non-tiring contraction. In conclusion, in the field of facial EMG processing, RMS features delivered the best performance while FCM classifier use as pattern recognition technique. In future, all popular classifier performances will be evaluated by applying RMS features as the main feature of EMG signals to find out which classifier is more suitable for facial EMG classification.

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