Electromyography Analysis for Person Identification

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Abstract

Physiological descriptions of the electromyography signal and other literature say that when we make a motion, the motor neurons of respective muscle get activated and all the innervated motor units in that zone produce motor unit action potential. These motor unit action potentials travel through the muscle fibers with conduction velocity and superimposed signal gets recorded at the electrode site. Here we have taken an analogy from the speech production system model as the excitation signal travels through vocal tract to produce speech; similarly, an impulse train of firing rate frequency goes through the system with impulse response of motor unit action potentials and travels along the muscle fiber of that person. As the vocal tract contains the speaker information, we can also separate the muscle fiber pattern part and motor unit discharge pattern through proper selection of features and its classification to identify the respective person. Cepstral and non uniform filter bank features models the variation in the spectrum of the signals. Vector quantization and Gaussian mixture model are the two techniques of pattern matching have been applied.

Keywords: Biometrics, Electromyogram, Gaussian mixture model (GMM), Identification, Vector Quantization.

1. INTRODUCTION

The EMG signal is the summation of the discharges of all the motor units within the pick-up range of the electrode. The nervous system always controls the muscle activity (contraction/relaxation). Hence, EMG signal is a complicated signal, which is controlled by the nervous system and is dependent on the anatomical and physiological properties of muscles. It is the study of muscle electrical signals. Muscle tissue conducts electrical potentials and the name given to these electrical signals is the muscle action potential. Surface EMG is a method of recording the information present in these muscle action potentials. When EMG is acquired from electrodes mounted directly on the skin, the signal is a composite of all the muscle fiber action potentials occurring in the muscles underlying the skin. These action potentials occur at random intervals. So at any one moment, the EMG signal may be either positive or negative voltage. Surface EMG signal consists of two major components. The First component is the firing frequency of the Motor Units. In the frequency domain, this component contributes spectral peaks which coincide with, and their quality depends on, the firing statistics of the individual MUs (Motor units). The spectral peaks are substantial at the mean frequency of the MUs firing frequencies, below 40 Hz, and have diminishing harmonics at the relatively higher frequencies [1], [2]. The second component is the resulting frequency spectra of the MUAP (motor unit action potential) shapes. This component is influenced heavily by the recording arrangement, type of electrode, distance between the electrodes, and the distance to the recorded fibers, as well as fiber distribution inside the muscle(motor unit recruitments), fatigue, etc. [3], [4], [5], [6]. In surface recording due to the filtering through skin layers and of the recording arrangements [3], Surface EMG signal reaches only into the few hundred Hz regions. Surface EMG, is the result of the surface recording of the superposition of the many MUs at the same time. The interference pattern generated by such a recording does not exactly retain the shape of the individual MU's. But its spectral content depicts the information about MUAP shape and other characteristics.

Human ECG has unique wave shape, amplitude, due to anatomical structure of the heart and physiological Conditions [7].many researchers used ECG for person identification and verification [8]. [9]. [10]. In the past ten years, several studies have been proposed using brain waves, e.g. EEG as a biometric modality. [11]. [12]. [13]. [14]. [15]. [16]. [17]. [18].

We focus on biometric recognition task of authentication of person based on Electromyogram (EMG) signal as a biological trait. To design the more resembling devices one needs to extract useful information from EMG signal in order to generate enough discrimination among different persons. Since direct connection between intact muscle, intact central nervous system and brain is unique to an individual, EMG signals vary from individual to individual. The EMG signal is directly related to the physiology of each individual. These measurements are influenced by physiologic factors which include muscle fiber pattern, motor unit discharge pattern, changes in blood flow in the muscle, force generating capacity of each muscle, neural activity, and neurotransmitter activity in different areas within the muscle, skin conductivity, position, shape and size of the muscle. The EMG signals have different signatures depending on age, muscle development, motor unit paths, different density of bone, heat distribution of the muscle, skin-fat layer, and gesture style. The external appearances of two people gestures might look identical, but the characteristic of EMG signals are different. Regardless of what factors originate differences in the measurement, the fact that the EMG contains physiologic dependant singularities potentiates its application to person identification.

The goals of this work were to (1) build a state-of-the-art person identification system based on myoelectric signals, (2) to address major issues in the novel technology that have not yet been addressed in literature and (3) to demonstrate the practicability of EMG based person identification. One important goal of this work was to explore appropriate feature extraction and classification methods in order to develop state-of-the-art EMG based person identification system that achieves recognition results comparable to those that have so far been reported in literature.

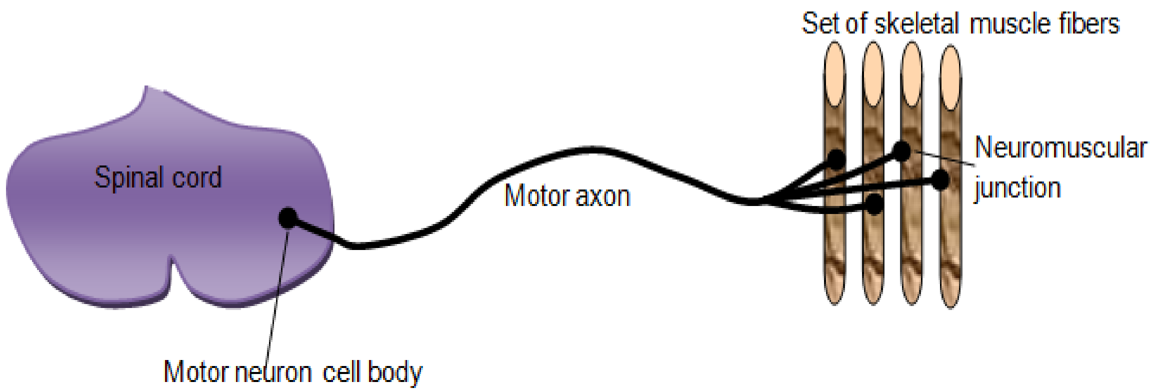
2 ANATOMICAL AND PHYSIOLOGICAL BASICS OF SURFACE ELECTROMYOGRAPHY (SEMG)

Skeletal muscle is the muscle attached to the skeleton. Its structural unit is the muscle fiber - an elongated cell ranging from 10 to 100 microns in diameter and from a few millimeters to 40cm in length [19]. Each muscle fiber is surrounded by a layer of connective tissue called endomysium. Groups of muscle fibers are wrapped by another layer of connective tissue called perimysium to form muscle bundles or fascicles. Skeletal muscles are composed of numerous fascicles. They are usually attached to bones via tendons composed of epimysium.

The contraction of skeletal muscle is controlled by the nervous system. Each muscle fiber can be Activated by one motor neuron (i.e. by one nerve) yet, one motor neuron can branch in up to several thousand branches, each one terminating in a different muscle fiber. A motor neuron and all the fibers it innervates are called a motor unit shown in fig.1. the term neuromuscular junction refers to the junction between a muscle fiber and the terminal of the motor neuron it is recruited by an ionic equilibrium between the inner and outer spaces of a muscle cell forms a resting potential at the muscle fiber membrane (approximately -80 to -90 mV when not contracted). The activation of an alpha-motor anterior horn cell (induced by the central nervous system or reflex) results in the conduction of a excitation along the motor nerve. After the release of transmitter substances at the motor endplates, an endplate potential is formed at the muscle fiber innervated by this motor unit. The diffusion characteristics of the muscle fiber membrane are briefly modified and Na+ ions flow in. This causes a membrane Depolarization which is immediately restored by backward exchange of ions within the active ion pump mechanism, the Repolarization. If a certain threshold level is exceeded within the Na+ influx, the depolarization of the membrane causes an Action potential to quickly change from – 80 mV up to 30 mV. Mono-polar electrical burst is immediately restored by the repolarization phase and followed by an after Hyper polarization period of the membrane. Starting from the motor end plates, the action potential spreads along the muscle fiber in both directions and inside the muscle fiber through a tubular system.

FIGURE 1: Motor Unit

3 EQUIPMENT FOR SURFACE EMG RECORDING



To develop EMG data acquisition system we employed an instrumentation amplifier INA 101 to reject common mode signals. A single order high pass filter of 10 Hz is used in the feedback of instrumentation amplifier output stage to prevent the saturation of data due to Base line noise and motion Artifact. Then to remove other low frequency noise such as ECG and other biomedical signal interference, sixth order unity gain Chebyshev Active High Pass Filter (20hz) and to remove high frequency thermal noise a fourth order Butterworth Active Low pass filter is employed (600hz).to overcome the problem with non-ideal operation of op-amps at high frequency one single order passive low pass RC filter is also employed. To remove line frequency components Notch filter is implemented using an active filter module UAF042 from Texas instruments is used. We acquired the filtered and Amplified EMG data through Line-In port of sound card through MATLAB.

4 PERSON SPECIFIC INFORMATION OF EMG SIGNAL

The EMG signal is very rich in information as it contains task specific, site specific, muscle specific, subject specific and person specific information Traditionally, skeletal muscle were classified based on their color as red fiber and white fiber. Also, depending upon twitch capabilities, fibers are classified as fast twitch and slow twitch fibers. These two main categories of fibers become three when the white fiber is split into two sections as Type-I(Red fibers, - slow oxidative or slow twitch or fatigue resistant) fiber characterized with slow ATP splitting rate, Type-IIa (Red fibers, also called fast twitch A – fast oxidative) fiber characterized with high ATP splitting rate and Type – II b (White fiber –Fast Glycolytic , also, called fast twitch B or fatigable) fiber characterized with low myoglobin content, few mitochondria, few blood capillaries, large amount of glycogen, very high rate of ATP splitting and fatigue easily compared to Type-I and Type-IIa fibers. Fiber types, force generating capacity of muscle, Motor unit discharge pattern, muscle fiber pattern vary considerably from muscle to muscle, and person to person and thus we have strong evidence that the EMG signal contains person specific information and is the objective of our work.

Motor unit discharge pattern is the source feature and the muscle fiber pattern is the system feature. By separating source and system feature similar to speaker identification using speech we can use EMG for person identification. However, appropriate EMG driven dynamic model is needed to be developed depending upon what information we need.

Any biologically assisted models commonly employ EMG as a means to monitor muscle activity. E.W.Theodo et all have developed an EMG assisted dynamic model which is unique in that it is person specific in terms of : 1) Anthrophometry (Muscle location and size), 2) Body mass characteristics, 3) Subject motion (inputs trunk as well as limb motion) and 4) Muscle activities[20]. Various EMG driven models to extract muscle specific information from EMG are discussed in [21]. Specific temporal change in the pattern of firing frequency that is depicted by spectral properties will be the model of person's muscle structure and this motivates to use EMG for person identification.

5 FEATURE EXTRACTION AND MODELING METHODS

5-1 Cepstral Features
Consider a given EMG waveform for a particular person. EMG frames of size 50 ms (100 samples for 2 kHz Signal) with a shift of 25 ms (50 samples for 2 kHz Signal) are taken. Therefore 400 frames for every ten second slot of EMG data obtained. In each session we have collected five slots of ten seconds each EMG data from all subjects. So for three sessions 6000 frames obtained.

5.2 Non Uniform Bank Features
Non uniform filter-bank: In this method, the signal spectrum will pass through a filter-bank set. The usage of these filter banks are motivated by the fact that, the EMG spectrum has some special shapes and are distributed by a non-linear scale in frequency domain. Using the filter-banks with spectral characteristics which are well-matched to those of the desired signal, the contribution of noise components in the frequency domain can be reduced. EMG spectrum is concentrated within the range of 20Hz-500Hz. In such a narrow band, full resolution is required to capture more information of the signal spectrum. In this work, EMG spectrum is simply processed by filtering out the frequency band outside the range of 20Hz-500Hz. non uniform filter bank extracts the corresponding bands of the input signal and has been widely used due to its consistent better performance.

5.3 Vector Quantization Modeling
The basic idea of using vector quantization is to compress a large number of cepstral vectors into a small set of code vectors. The VQ codebook is usually trained with the LBG algorithm to minimize the quantization error when replacing all feature vectors with their corresponding nearest code vectors. The Euclidean distance is often used as a quantization error measure.

5.4 Gaussians Mixture Modeling
GMMs are employed in various fields such as clustering and classification, but unlike k-means, they are able to build soft clustering boundaries i.e., points in space can belong to any class with a given probability and have the ability to represent smooth approximations for general probability density functions through the weighted sum of a finite number of Gaussian densities. The standard method used to fit a GMM to observe data is the expectation maximization (EM) algorithm [22], which converges to a maximum likelihood (ML) estimate. Plus several model order selection used to estimate the number of components of a GMM. GMMs are used to model the likelihoods of the features extracted from the EMG signal. GMMs are well-known flexible modeling tools able to approximate any probability density function.

6 EXPERIMENTAL RESULTS AND DISCUSSION

The EMG data is collected in three sessions with time gap of one day for a population of 49 (30 healthy male plus 19 female) subjects by placing the electrode at the same location on the Flexor carpi ulnaris muscle present in the forearm for all sessions. In each session, five slots of ten second each EMG data per subject are acquired. For EMG frame of 50 ms with an overlap of 25 ms 40 frames per second and 400 frames per 10 second slot are obtained. We have used first four slots (1600 frames) of all the subjects of randomly selected any two sessions data (that is 3200 frames) for training using vector quantization and Gaussian mixture model. Last fifth slot of data (400 frames) in all three sessions of 49 subjects was used for testing individually for different code book size in case of VQ and number of Gaussians in case of GMM. The following configurations using different combinations of features tested are

1) 39 dimensional base cepstra with VQ
2) 13 dimensional base cepstra plus 13 delta 13 delta with VQ
3) 13 dimensional base non uniform filter bank plus 13 delta and13 acceleration coefficients with VQ
4) 13 dimensional base non uniform filter bank plus 13 delta and 13 acceleration coefficients with GMM

A result of person identification using different combinations of features tested with VQ and GMM are tabulated in Table 1-4. As it can be seen in the table 1, we have explored that the VQ-based system achieved the best result of 93.8776% using the configuration with 39 dimensional base cepstra. Table 2 shows that, for the VQ-based system with 13 dimensional base cepstra plus 13 delta and 13 acceleration coefficients, the best score was 85.7143%, also using same set of features. Table 2-3 show that, In both cepstral based system and non uniform filter bank based system with VQ, the non uniform filter bank based system give higher person identification performance than cepstral based system. The reason is, in non uniform filter bank full resolution can be achieved to capture the more information present in the EMG signal. Based on the information present in EMG signal the non uniform filters bank extracts more hidden information. As it can be seen in the Table 4, GMM-based system achieved the best result of 97.9592% using 13 dimensional base non uniform filter bank plus 13 delta and 13 acceleration coefficients. For the VQ-based system with 39 dimensional non uniform filter banks, the best score was 93.8776%, also using same set of features. Further non uniform filter bank with GMM is exhibiting more effectiveness than the non uniform filter bank with VQ, because one of the powerful attributes of GMM is its ability to form smooth approximations to arbitrarily shaped densities and the individual component densities may model some underlying set of hidden classes. GMM also captures uncertainty in cluster assignments. In our experiment we have determined the optimal choice of code book size as 16, 32, 64 with VQ and Gaussians size as 2, 4, 8, 16, and 32 with GMM. For smaller number of Gaussian components in GMM good person identification performance obtained. This suggests that the non uniform filter bank coefficients with GMM are useful parametric measures from a biometric perspective and that they can be used to identify subjects.

EMG based person identification system using 39 dimensional base Cestrum-VQ approach provides average person identification performance of about 65.3050%, 13 dimensional base cepstra plus 13 delta 13 delta-VQ approach of about 58.9569%, filter bank - VQ approach of about 72.1088% including all untrained sessions of all code book sizes and Filter bank-GMM approach of about 73.3333% including all untrained sessions of all Gaussians mixtures. The results indicate that the EMG has significant biometric potential.

Training sessions	Code book size	Testing session		
		1	2	3
1,2	16	57.1429	93.8776	71.4286
	32	59.1837	93.8776	69.3878
	64	55.1020	91.8367	65.3061
2,3	16	57.1429	75.5102	91.8367
	32	53.0612	71.4286	87.7551
	64	51.0204	67.3469	89.7959
1,3	16	59.1837	77.55	91.8367
	32	55.1020	71.4286	87.7551
	64	51.204	71.4286	89.7959

TABLE 1: Results of Person Identification using 39 Dimensional Base Cepstra with VQ

Training sessions	Code book size	Testing session		
		1	2	3
1,2	16	55.1020	77.5510	63.2653
	32	59.1837	83.6735	61.2245
	64	55.1020	79.5918	57.1429
2,3	16	44.8980	69.3878	85.7143
	32	46.9388	69.3878	83.6735
	64	44.8980	69.3878	81.6327
1,3	16	44.8980	69.3878	85.7143
	32	46.9388	71.4286	83.6735
	64	44.8980	71.4286	81.6327

TABLE 2: Results of Person Identification using 13 Dimensional Base Cepstra plus 13 Delta 13 Delta with VQ

Training sessions	Code book size	Testing session		
		1	2	3
1,2	16	67.3469	93.8776	67.3469
	32	69.3878	93.8776	69.3878
	64	69.3878	93.8776	71.4286
2,3	16	63.2653	81.6327	91.8367
	32	63.2653	81.6327	91.8367
	64	67.3469	79.5918	91.8367
1,3	16	63.2653	83.6735	91.8367
	32	63.2653	81.6327	91.8367
	64	67.3469	81.6327	91.8367

TABLE 3: Results of Person Identification using 13 Dimensional Base Non uniform Filter Bank plus 13 Delta 13Delta with VQ

Training sessions	Number of Gaussians	Testing session		
		1	2	3
1,2	2	63.2653	97.9592	73.4694
	4	69.3878	97.9592	73.4694
	8	71.4286	95.9184	75.5102
	16	69.3878	97.9592	75.5102
	32	69.3878	97.9592	73.4694
2,3	2	57.1429	81.6300	91.8367
	4	63.2653	79.5918	97.9592
	8	65.3061	83.6735	97.9592
	16	65.3061	83.6735	97.9592
	32	65.3061	85.7143	95.9184
1,3	2	57.1429	81.6327	91.8367
	4	65.3061	77.5510	97.9592
	8	65.3061	83.6735	97.9592
	16	63.2653	83.6735	97.9592
	32	65.3061	85.7143	95.9184

TABLE 4: Results of Person Identification using 13 Dimensional Base Non uniform Filter Bank plus 13 Delta 13Delta with GMM

6 CONCLUSION

The proposed cepstral features, non uniform filter bank features and the associated modeling techniques have been shown to be suitable for the EMG in the human identification task, yielding a relatively good result in the experimental evaluation.

The results obtained in the present work corroborate the long existing line of research showing evidence that EMG carrying individual-specific information which can be successfully exploited for purpose of person identification.

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