FREQUENCY DOMAIN ANALYSIS OF ELECTROMYOGRAPHY SIGNALS FROM FACIAL MUSCLES WITH NEURAL NETWORKS

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***Abstract*— EMG signal is a complicated signal, which is controlled by the nervous system. Quantitative analysis in clinical electromyography (EMG) is very desirable because it allows a more standardized, sensitive and specific evaluation of the neurophysiologic findings, especially for the assessment of neuromuscular disorders.. In this study, we have investigated that, The analysis of different electromyography signals (NOR & MYO). This paper basically deals with the basic steps for recording, analysis of EMG signal,. For recording of EMG of a muscles or facial muscles two electrodes are used one is surface electrodes and second one is needle electrode, after comparing both electrodes we found surface electrode is better than needle electrode .The analysis the EMG signal during three phase segmentation ,classification and feature extraction. We extracted both time domain (TPDs) and frequency domain parameters (FDPs),by which we get some important information of MUAP abnormality and muscular change. and we also concluded its best application for recognition of Facial Expression . Facial expression analysis is rapidly becoming an area of intense interest in computer science and human-computer interaction design communities. The most expressive way humans display emotions is through facial expressions.**

Keywords- EMG; TPD; Facial Expression.

INTRODUCTION

Small electrical currents are generated by muscle fibres prior to the production of muscle force. These currents are generated by the exchange of ions across muscle fibre membranes, a part of the signaling process for the muscle fibres to contract. The signal called the electromyogram (EMG) can be measured by applying conductive elements or electrodes to the skin surface, or invasively within the muscle. Surface EMG is the more common method of measurement, since it is non-invasive and can be conducted by personnel other than Medical Doctors, with minimal risk to the subject. Measuring and accurately representing the sEMG signal depends on the properties of the electrodes and their interaction with the skin, amplifier design, and the conversion and subsequent storage of the EMG signal from analog to digital form (i.e. A/D conversion). The quality of the measured EMG is often described by the ratio between the measured EMG signal and unwanted noise contributions from the environment. The goal is to maximize the amplitude of the signal while minimizing the noise. Assuming that the amplifier design and process of A/D conversion exceed acceptable standards, the signal to noise ratio is determined almost exclusively by the electrodes, and more specifically, the properties of the electrode – electrolyte – skin contact.

ELECTROMYOGRAPHIC SIGNALS FROM FACIAL MUSCLES WITH NEURAL NETWORKS

Over the last decade, automatic facial expression analysis has become an active research area that 0nds potential applications in areas such as more engaging human–computer interfaces, talking heads, image retrieval and human emotion analysis. Facial expressions reflect not only emotions, but other mental activities, social interaction and physiological signals. In this survey, we introduce the most prominent automatic facial expression analysis methods and systems presented in the literature. Facial motion and deformation extraction approaches as well as classi0cation methods are discussed with respect to issues such as face normalization, facial expression dynamics and facial expression intensity, but also with regard to their robustness towards environmental changes.

Facial expressions are the facial changes in response to a person's internal emotional states, intentions, or social communications. Facial expression analysis has been an active research topic for behavioral scientists since the work of Darwin in 1872.

Facial expression analysis refers to computer systems that attempt to automatically analyze and recognize facial motions and facial feature changes from visual information. Sometimes the facial expression analysis has been confused with emotion analysis in the computer vision domain. For emotion analysis, higher level knowledge is required. For example, although facial expressions can convey emotion, they can also express intention, cognitive processes, physical effort, or other intra- or interpersonal meanings. Interpretation is aided by context, body gesture, voice, individual differences, and cultural factors as well as by facial configuration and timing [10, 67, 68]. Computer facial expression analysis systems need to analyze the facial actions regardless of context, culture, gender, and so on. The accomplishments in the related areas such as psychological studies, human movement analysis, face detection, face tracking, and recognition make the automatic facial expression analysis possible. Automatic facial expression analysis can be applied in many areas such as emotion and paralinguistic communication, clinical psychology, psychiatry, neurology, pain assessment, lie detection, intelligent environments, and multimodal human computer interface (HCI). Many of the most important issues relating to the acquisition and analysis of the sEMG signal were recently addressed in a multi-national consensus initiative called SENIAM: Surface EMG for the Non-Invasive Assessment of Muscles.

Fig. 1.1 Emotion-specified facial expression (1.Disgust; 2,Fear;3,Joy;4,Surprise;5,Sadness;6,Anger

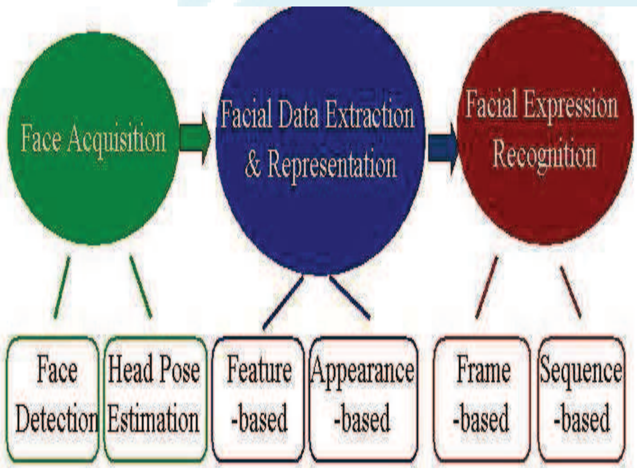


Fig. 1.2 Basic structure of facial expression analysis systems

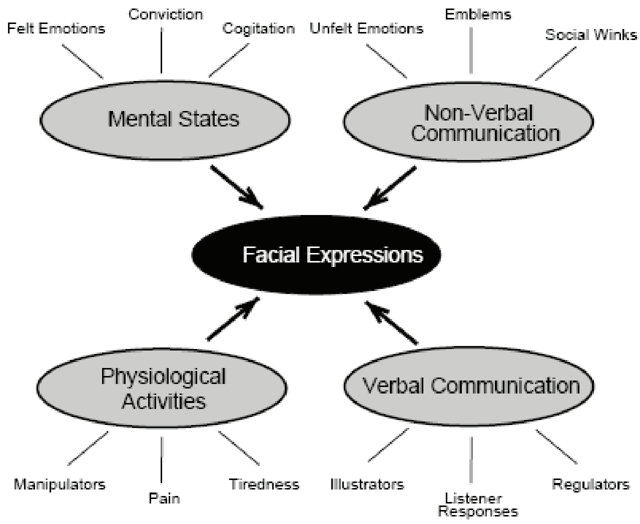


Fig. 1. Sources of facial expressions.

(i)Ambient Noise

Ambient noise is generated by electromagnetic devices such as computers, force plates,power lines etc. Essentially any device that is plugged into the wall A/C (Alternating Current) outlet emits ambient noise. This noise has a wide range of frequency components, however, the dominant frequency component is 50Hz or 60Hz,corresponding to the frequency of the A/C power supply (i.e. wall outlet).

(ii)Transducer Noise

Transducer noise is generated at the electrode – skin junction. Electrodes serve to convert the ionic currents generated in muscles into an electronic current that can be manipulated with electronic circuits and stored in either analog or digital form as a voltage potential. There are two types of noise sources that result from this transduction from an ionic to an electronic form:

- D/C (Direct Current) Voltage Potential: caused by differences in the impedance between the skin and the electrode sensor, and from oxidative and reductive chemical reactions taking place in the contact region between the electrode and the conductive gel (Gerdle et al., 1999)
- A/C (Alternating Current) Voltage Potential: generated by factors such as fluctuations in impedance between the conductive transducer and the skin. One effective method to decrease impedance effects is to use Ag-AgCl electrodes. This electrode consists of a silver metal surface plated with a thin layer of silver chloride material. (Duchene & Goubel, 1993) The goal with EMG measurements is to maximize the signal to noise ratio. Technological developments have decreased the level of noise in the EMG signal. The most important development was the introduction of the bipolar recording technique. Bipolar electrode arrangements are used with a

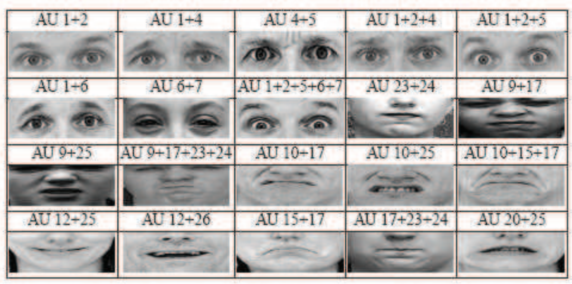
differential amplifier, which functions to suppress signals common to both electrodes. Essentially, differential amplification subtracts the potential at one electrode from that at the other electrode and then amplifies the difference. Correlated signals common to both sites, such as from power sources and electromagnetic devices, but also EMG signals from more distant muscles are suppressed. Moreover, the D/C components such as the over-potential generated at the electrode skin junction will be detected with similar amplitude (see below) and will therefore be suppressed. In contrast, signals from muscle tissue close to the electrodes will not be correlated and will be amplified (Gerdle et al., 1999). The advent of bipolar recordings with differential pre-amplification has enabled the recording of the full EMG bandwidth while increasing the spatial resolution (i.e. the size of the recording area). This also has the effect of increasing the signal to noise ratio. One remaining factor is how the quality of the electrode – skin contact impacts the process of differential amplification in bipolar EMG measurements. The electrode – skin contact is quantitatively defined by the resistance of the skin and underlying tissues, in addition to the capacitance of the electrodes. It is commonly called electrode – skin impedance. The electrode – skin impedance can be measured quantitatively, such as with the BISIM impedance measurement device offered by Bortec.

Problem Space for Facial Expression Analysis

With few exceptions [17, 20, 30, 81], most AFEA systems attempt to recognize a small set of prototypic emotional expressions as shown in Fig. 1.1, (i.e., disgust, fear, joy, surprise, sadness, anger). This practice may follow from the work of Darwin [18] and more recently Ekman and Friesen [23, 24] and Izard et al. [42] who proposed that emotion-specified expressions have corresponding prototypic facial expressions. In everyday life, however, such prototypic expressions occur relatively infrequently. Instead, emotion more often is communicated by subtle changes in one or a few discrete facial features, such as tightening of the lips in anger or obliquely lowering the lip corners in sadness. Change in isolated features, especially in the area of the eyebrows or eyelids, is typical of paralinguistic displays; for instance, raising the brows signals greeting [21]. To capture such subtlety of human emotion and paralinguistic communication, automated recognition of fine-grained changes in facial expression is needed. The facial action coding system (FACS: [25]) is a human-observer-based system designed to detect subtle changes in facial features. Viewing videotaped facial behavior in slow motion, trained observers can manually FACS code all possible facial displays, which are referred to as action units and may occur individually or in combinations. FACS consists of 44 action units. Thirty are anatomically related to contraction of a specific set of facial muscles (Table 11.1) [22]. The anatomic basis of the remaining 14 is unspecified (Table 11.2). These 14 are referred to in FACS as miscellaneous actions. Many action units may be coded as symmetrical or asymmetrical. For action units that vary in intensity, a 5-point ordinal scale is used to measure the degree of muscle contraction. Table 11.3 shows some examples of combinations of FACS action units. Although Elman and Friesen proposed that specific combinations of FACS action units represent prototypic expressions of emotion, emotion-specified expressions are not part of FACS; they are coded in separate systems, such as the emotional facial action system (EMFACS).

Table 1.4 FACS action units (AU). AUs with "*" indicate that the criteria have changed for this AU, that is, AU 25, 26, and 27 are now coded according to criteria of intensity (25A-E), and AU 41, 42, and 43 are now coded according to criteria of intensity. FACS itself is purely descriptive and includes no inferential labels. By converting FACS codes to EMFACS or similar systems, face images may be coded for emotion-specified expressions as well as for more molar categories of positive or negative emotion.

Table 11.3. Some examples of combination of FACS action units.



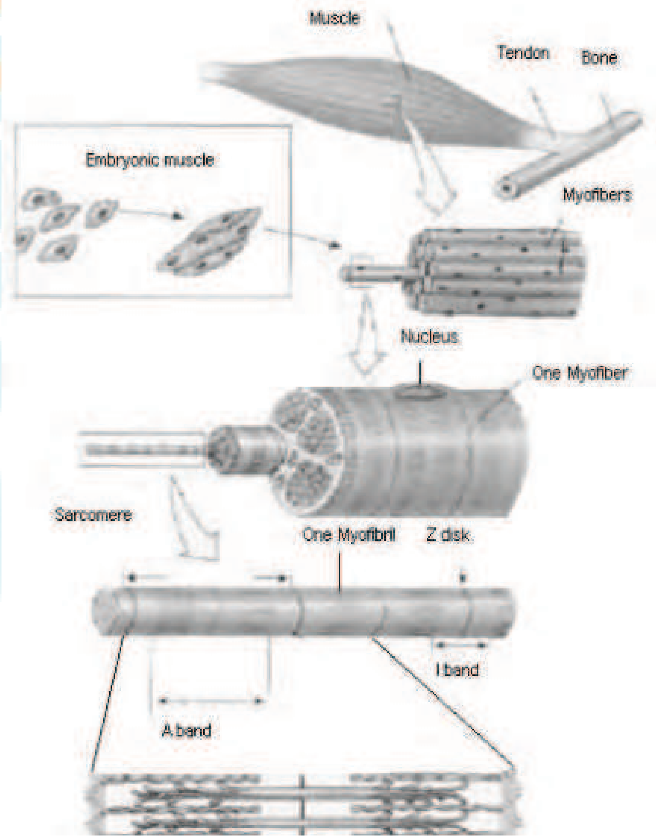
DIFFERENT EMG SIGNALS

EMG signal is a complicated signal, which is controlled by the nervous system. Quantitative analysis in clinical electromyography (EMG) is very desirable because it allows a more standardized, sensitive and specific evaluation of the neurophysiologic findings, especially for the assessment of neuromuscular disorders.. In this study, we have investigated that, The analysis of different electromyography signals (NOR & MYO). This paper basically deals with the basic steps for recording, analysis of EMG signal,. For recording of EMG of a muscles or facial muscles two electrodes are used one is surface electrodes and second one is needle electrode, after comparing both electrodes we found surface electrode is better than needle electrode .The analysis the EMG signal during three phase segmentation ,classification and feature extraction. We extracted both time domain (TPDs) and frequency domain parameters (FDPs), by which we get some important information of MUAP abnormality and muscular change. and we also concluded its best application for recognition of Facial Expression . Facial expression analysis is rapidly becoming an area of intense interest in computer science and human-computer interaction design communities. The most expressive way humans display emotions is through facial expressions.

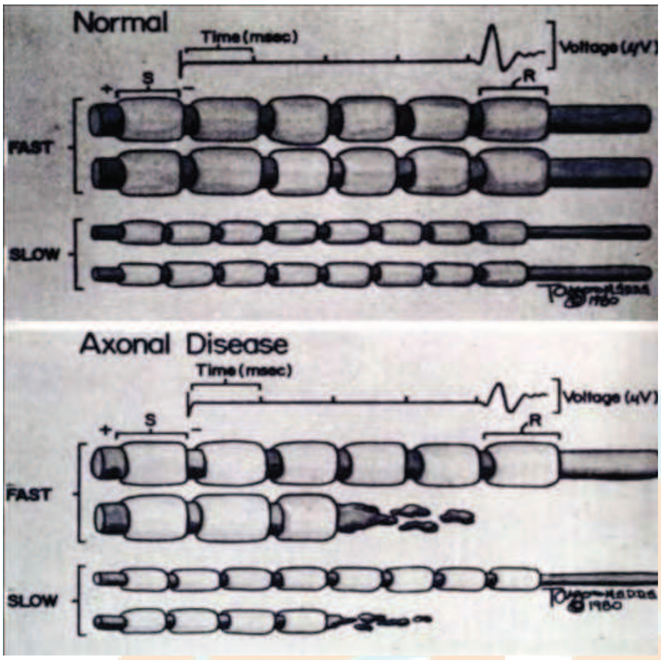
i. Signal

STRUCTURAL reorganization of the motor unit, the smallest functional unit of muscle, takes place because of disorders affecting peripheral nerve and muscle. Motor unit morphology can be studied by recording its electrical activity, the procedure known as electromyography (EMG). The study of electromyography (EMG) signals is a study of the electrical properties and activities of muscle tissue. EMG signals are detected by placing an electrode into, or over a muscle and detecting the extracellular voltages produced by the electrical activity of the muscle fibers. The analysis of EMG signals detected during muscle contraction provides important information to aid in the diagnosis and characterization of neuromuscular disorders. Clinical electromyography is the study of the function of the neuromuscular system through the analysis of EMG signals. In general, the characteristics of EMG signals are dependent on a number of factors, including the anatomical and physiological of the related neuromuscular system, the level of muscle contraction, the type of electrode used and the location of the electrode relative to the contracting muscle fibers. Basically the analysis of the EMG signal is based on its basic constituent i.e.motor unit action potentials (MUAPs) .The motor unit is the smallest functional unit of a muscle which can be activated voluntarily. It consists of group of muscle fibers which are innervated from the same motor nerve. With increasing muscle force, the EMG signal shows an increase in number of activated MUAPs recruited at increasing firing rate, making it difficult for neurophysiologist to distinguish individual MUAP waveforms. Emg signals are the superposition of multiple motor unit action potentials (MUAPTs).The electrical signal the emits from the activation of the muscle fibers of a motor unit is called MUAP and in order to sustain a muscle contraction, the motor unit (MU) has to be activated repeatedly, the resulting sequence of MUAP is called a MUAPTs.

The physiological and Anatomical structure of muscle fiber shows in (Fig-1).muscles can make by the group of number of muscles fiber & tissues. Single muscle fiber potentials arrive with mutual time differences at a plane normal to the muscle axis. This is attributing to propagation times in the terminal nerve endings, neuromuscular transmission delays at the motor end plates. In (Fig-2) we can see that the conduction response of the nerve here two types of conduction are showing, upper one is normal condition and lower one is diseased conduction. In diseased conduction the nerves are damaged which resulting poor nerve condition. The information extracted from the EMG recordings is of great clinical importance and is used for the diagnosis and treatment of neuromuscular disorders .



[fig-1] Physiological & Anatomical structure of muscle fibers



[Fig-2] Nerve conduction response

RESULTS AND DISCUSSION

Four recent trends in automatic facial expression analysis are (1) diversity of facial features in an effort to increase the number of expressions that may be recognized; (2) recognition of facial action units and their combinations rather than more global and easily identified emotion specified expressions; (3) more robust systems for face acquisition, facial data extraction and representation, and facial expression recognition to handle head motion (both in-plane and out-of-plane), occlusion, lighting change, and low intensity expressions, all of which are common in spontaneous facial behavior in naturalistic environments; and (4) fully automatic and real-time AFEA systems. All of these developments move AFEA toward real-life applications. A public database (Cohn-Kanade AU-Coded Face Expression Image Database [43]) that addresses most problems for deliberate facial expression analysis has become widely used by many researchers to conduct comparative tests of their methods. Comparable image databases with ground-truth labels, preferably both action units and emotion-specified expressions, are needed for the next generation of systems, which are intended for naturally occurring behavior in real-life settings. For directed facial action tasks or other posed facial expressions, the CMU S1 system [81, 82, 83] can recognize the largest number of AUs whether they occur alone or in combinations. The system uses two neural networks (one for the upper face and one for the lower face). In recognizing whether AUs occur alone or in combinations, the system is performing a perceptual task analogous to that of human observers, who can recognize facial actions occurring in novel contexts. For spontaneous expression analysis, promising results have been achieved for a few AUs by CMU [14, 57] and UCSD [3] systems. Work in spontaneous facial expression analysis is just now emerging and potentially will have significant impact across a range of theoretical and applied topics. Although many recent advances and successes in automatic facial expression analysis have been achieved, as described in the previous sections, many questions remain open, for which answers must be found. Some major points are considered here.

1. How do humans correctly recognize facial expressions?

Research on human perception and cognition has been conducted for many years, but it is still unclear how humans recognize facial expressions. Which types of parameters are used by humans and how are they processed? By comparing human and automatic facial expression recognition we may be able advance our understanding of each and discover new ways of improving automatic facial expression recognition.

2. Is it always better to analyze finer levels of expression?

Although it is often assumed that more fine-grained recognition is preferable, the answer depends on both the quality of the face images and the type of application. Ideally, an AFEA system should recognize all action units and their combinations. In high quality images, this goal seems achievable; emotion-specified expressions then can be identified based on emotion prototypes identified in the psychology literature. For each emotion, prototypic action units have been identified. In lower quality image data, only a subset of action units and emotion specified expression may be recognized. Recognition of emotion-specified expressions directly may be needed. We seek systems that become 'self aware' about the degree of recognition that is possible based on the information of given images and adjust processing and outputs accordingly. Recognition from coarse-to-fine, for example from emotion-specified expressions to subtle action units, depends on image quality and the type of application. Indeed, for some purposes, it may be sufficient that a system is able to distinguish between positive, neutral, and negative expression, or recognize only a limited number of target action units, such as brow lowering to signal confusion, cognitive effort, or negative effect.

3. Is there any better way to code facial expressions for computer systems?

Almost all the existing work has focused on recognition of facial expression, either emotion specified expressions or FACS coded action units. The emotion-specified expressions describe expressions at a coarse level and are not sufficient for some applications. Although the FACS was designed to detect subtle changes in facial features, it is a human-observer-based system with only limited ability to distinguish intensity variation. Intensity variation is scored at an ordinal level; the interval level measurement is not defined and anchor points may be subjective. Challenges remain in designing a computer-based facial expression coding system with more quantitative definitions.

4. How do we obtain reliable ground truth?

Whereas some approaches have used FACS, which is a criterion measure widely used in the psychology community for facial expression analysis, most vision-based work uses emotion specified expressions. A problem is that emotion-specified expressions are not well defined. The same label may apply to very different facial expressions, and different labels may refer to the same expressions, which confounds system comparisons. Another problem is that the reliability of labels typically is unknown. With few exceptions, investigators have failed to report inter observer reliability and the validity of the facial expressions they have analyzed. Often there is no way to know whether subjects actually showed the target expression or whether two or more judges would agree that the subject showed the target expression. At a minimum, investigators should make explicit labeling criteria and report inter observer agreement for the labels. When the dynamics of facial expression are of interest, temporal resolution should be reported as well. Because intensity and duration measurements are critical, it is important to include descriptive data on these features as well. Unless adequate data about stimuli are reported, discrepancies across studies are difficult to interpret. Such discrepancies could be due to algorithms or to errors in ground truth determination.

5. How do we recognize facial expressions in real life?

Real-life facial expression analysis is much more difficult than the posed actions studied predominantly to date. Head motion, low resolution input images, absence of a neutral face for comparison, and low intensity expressions are among the factors that complicate facial expression analysis. Recent works in 3D modeling of spontaneous head motion and action unit recognition in spontaneous facial behavior are exciting developments. How elaborate a head model is required in such work is as yet a research question. A cylindrical model is relatively robust and has proven effective as a part of blink detection system, but highly parametric, generic, or even custom-fitted head models may prove necessary for more complete action unit recognition. Most work to date has used a single, passive camera. Although there are clear advantages to approaches that require only a single passive camera or video source, multiple cameras are feasible in a number of settings and can be expected to provide improved accuracy. Active cameras can be used to acquire high resolution face images. Also, the techniques of super resolution can be used to obtain higher resolution images from multiple low resolution images. At present, it is an open question how to recognize expressions in situations in which a neutral face is unavailable, expressions are of low intensity, or other facial or nonverbal behaviors, such as occlusion by the hands, are present.

6. How do we best use the temporal information?

Almost all work has emphasized recognition of discrete facial expressions, whether defined as emotion-specified expressions or action units. The timing of facial actions may be as important as their configuration. Recent work by our group has shown that intensity and duration of expression vary with context and that the timing of these parameters is highly consistent with automatic movement [73]. Related work suggests that spontaneous and deliberate facial expressions may be discriminated in terms of timing parameters [16], which is consistent with neuropsychological models [63] and may be important to lie detection efforts. Attention to timing also is important in guiding the behavior of computer avatars. Without veridical timing, believable avatars and ones that convey intended emotions and communicative intents may be difficult to achieve.

7. How may we integrate facial expression analysis with other modalities?

Facial expression is one of several modes of nonverbal communication. The message value of various modes may differ depending on context and may be congruent or discrepant with each other. An interesting research topic is the integration of facial expression analysis with that of gesture, prosody, and speech. Combining facial features with acoustic features would help to separate the effects of facial actions due to facial expression and those due to speech related movements. The combination of facial expression and speech can be used to improve speech recognition and multimodal person identification.

References

S. Boisset, F Goubel, "Integrated electromyography activity and muscle work," J Applied Physiology, vol 35, pp. 695-702, 1972.

BISHOP, C. M. 1996. *Neural Networks for Pattern Recognition.* Oxford University Press, New York.CASINI, A., PERINI, S., STARITA, A., AND BLANC, Y. 1998. Evaluation and classification of surface EMG signals in gait analysis.In *Proceedings of Third International Conference of Neural Networks and Expert Systems in Medicine and Healthcare.* World Scientific, Singapore. 74–82.

LAAKSO, J., JUHOLA, M., AND SURAKKA, V. 2002. Neural network recognition of electromyography signals of two facial muscle sites. In *Proceedings of Medical Informatics Europe* 2002, 83–87.

E. A. Clancy, E. L. Morin, and R. Merletti, "Sampling, Noise reduction and Amplitude Estimation Issues in Surface Electro Electromyography, *"Journal of Electromyography and Kinesiology,* vol. 12,no. 1, pp. 1-16, Feb 2002, doi:10.1016/S1050-6411(01)00033-5.

P. Ekman, W.V. Friesen, Facial Action Coding System: A Technique for the Measurement of Facial Movement, Consulting Psychologists Press, Palo Alto, 1978.

CASINI, A., PERINI, S., STARITA, A., AND BLANC, Y. 1998. Evaluation and classification of surface EMG signals in gait analysis.

In Proceedings of Third International Conference of Neural Networks and Expert Systems in Medicine and Healthcare. World Scientific, Singapore. 74–82.

R. S. LeFever and C. J. De Luca, "A procedure for decomposing the myoelectric signal into its constituent action potentials," IEEE

Trans. Biomed. Eng., vol. BME-29, pp. 149-153; pp 158-164, March 1982.

E. A. Clancy and N. Hogan, "Theoretic and Experimental Comparison of Root-Mean-Square and Mean-Absolute-Value Electromyogram Amplitude Detectors," *Proc. nineteenth Annu.Int. Conf. IEEE Engineering in Medicine and Biology Society (EMBS'97)*,pp. 1267-1270, vol. 3, Oct.-Nov. 1997, doi:10.1109/IEMBS.1997.756605.

Basmajian JV, De Luca CJ (1985) Muscles Alive. Their Function Revealed by Electromyography. Williams & Wilkens, Baltimore.