International Journal of Scientific and Technical Advancements
ISSN: 2454-1532

Effect of Fatigue on Speech and EMG Signals Generated in Zygomaticus Muscles

Jang Bahadur Singh, Sandeep Arya, Parveen Kumar Lehana
D.S.P. Lab, Dept. of Physics and Electronics, University of Jammu, J&K, India
Email: sonajbs@gmail.com

***Abstract*—**Emotional arousal can cause changes in respiration pattern and muscle stress in the vocal tract during speech production. Many researchers confirm that during muscular fatigue, there is a shift of the power spectrum toward lower frequencies and an increase in the root mean square amplitude of the EMG signal. In this paper, investigations were carried out analyze the effect of fatigue on speech and facial EMG signals at zygomaticus muscle on the basis of spectrograms and LSD techniques. It can be concluded that speech signals show better results than EMG signals.

***Keywords*—** Electromyography; Fatigue; Log Spectral Distance; Speech production; Zygomaticus muscle

I. Introduction

Speech production comprises many psychological and physical processes [1]. Beside linguistic information, speech signal also convey lot of information about the speaker identity such as: gender, age, health and emotional state [2]. Stress and its detection on speech signals has been the subject of many studies [3]. The factors causing stress can be due to adverse environments, such as noisy backgrounds, emergency conditions, high workload stress, multitasking, fatigue due to sustained operation, physical environmental factors, emotional moods, etc. Various investigations [4-7] have shown distinctive differences in phonetic features between normal and speech produced under Lombard effect. Moreover, emotional arousal can cause changes in respiration pattern and muscle tension in the vocal tract. Such changes in speech production brought on by a variety of emotions have been the focus of number of research investigations [8-10]. Stress classification performance using these features was determined using separability distance metrics and neural network based classifiers. Other acoustic features helpful to indicate stress on speech include fundamental frequency (*f0*), phoneme duration and intensity, glottal source structure (especially spectral slope), and vocal tract formant structure [3], [10]. Fatigue related cognitive-physiological change may affect the muscle tension and body temperature which can indirectly influence speech characteristics [1].

The recording and analysis of the electrical movement of a contracting muscle is termed as Electromyography (EMG). It helps in determining the neuromuscular diseases. Needle or surface based electrodes are used to detect such signals [11]. In order to detect and analysis the raw EMG signals commonly used parameters are: the root mean squared (RMS) value and the average rectified value. Many mathematical models such as wavelet transform (WT), time-frequency approaches, Fourier transform, Wigner-Ville distribution, statistical measures, and higher-order statistics were also used. It is important to note that the selection of suitable processing technique depends on the physiological characteristics of the muscles [12]. Various applications of surface electromyography (SEMG) include estimation of muscle fiber conduction velocity, diagnosis, and clinical application with new electrode design, biomechanics and motion analysis, speech recognition, and prosthetic device development [13]. Fatigue in a muscle is revealed by a few changes in its EMG signal in either the time or frequency domains [14, 15]. Recording of EMG signals under dynamic conditions, the frequency content of the signal continuously changes over time. Non-stationery signals of the surface EMG can be distinguished as slow or fast non-stationeries. The slow non-stationeries are mostly due to the accumulation of metabolites that causes the electrical manifestations of muscle fatigue while fast non-stationeries are mainly related to the biomechanics of the task. Thus the variations in muscle force cause a variation of the frequency content of the signal [16]. Besides, due to body movement, there is relative displacement of the electrodes with respect to the underlying muscle fibers, which also affects the frequency content of the signal [17]. Therefore Cohen class time-frequency transforms have also been used by researchers for better processing surface EMG signals under dynamic conditions [18, 19]. Thus EMG signals have been used widely to illustrate changes in muscle function during fatigue. Many researchers confirm that during muscular fatigue, there is a shift of the power spectrum toward lower frequencies and an increase in RMS amplitude of the EMG signal [20, 21].

However, little empirical research has been done to study the comparison between fatigue, speech and EMG features. The objective of the paper is to study the effect of fatigue on speech and EMG signals generated in zygomaticus muscle. The methodology of the investigation is given in Section II. The results and discussions are presented in Section III. Finally conclusion is described in Section IV.

II. Methodology

In order to investigate the effect of facial EMG patterns along with speech with time, the experiment was conducted with six subjects Sp1 to Sp6 (three males and three females) having age between 22-28 years. Speech signal was recorded with the help of microphone attached to audio amplifier

Jang Bahadur Singh, Sandeep Arya, and Parveen Kumar Lehana, "Effect of fatigue on speech and EMG signals generated in zygomaticus muscles," *International Journal of Scientific and Technical Advancements*, Volume 2, Issue 4, pp. 49-52, 2016.

(LM386). The microphone was fixed at distance of about 5 cm from the mouth. EMG signals from the zygomaticus minor, zygomaticus major and common reference points on the face were recorded with silver–silver chloride surface electrodes (8 mm electrode diameter). Fig 1 shows electrode location on facial muscles. All electrode pairs were placed in a direction parallel to the general direction of muscle fibers for a given muscle. EMG signals were fed into a differential amplifier with adjustable gain setting of amplifier and low pass filter. USB based Data acquisition module was used with 12-bits and 150 kS/s resolution.

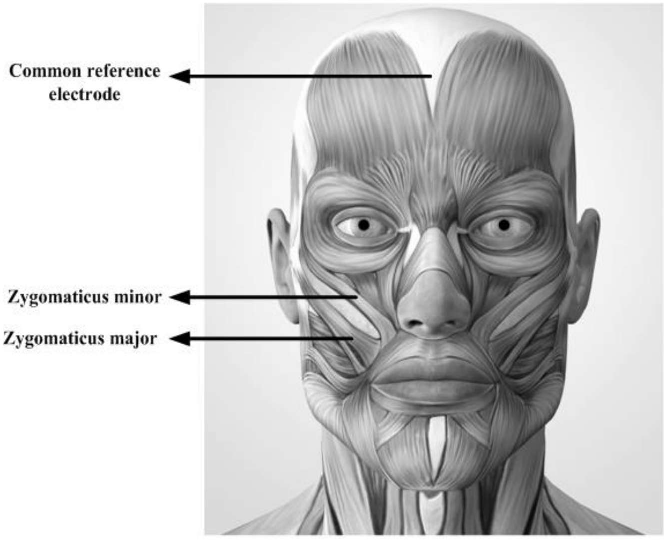


Fig. 1. Electrode position points for EMG signals.

The speakers were asked to repeat the phrase for 15 minutes continuously. The speech signals and the corresponding EMG signals were recorded simultaneously using a data acquisition system. On an average 180 samples of signals were recorded from each speaker. The recorded signals were segmented manually into separate files, after an interval of one minute. The signals were analyzed using time-domain patterns, spectrograms, and mean log-spectral-distances (LSD). Fig. 2 represents the block diagram of the experimental setup.

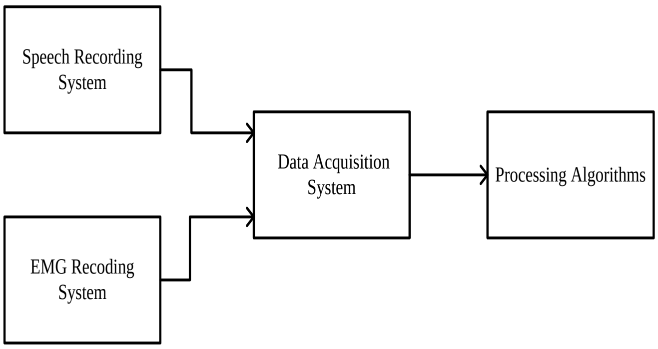


Fig. 2. Block diagram of experimental setup.

III. Results and Discussion

Investigations were carried out on facial EMG and speech signals on the basis of spectrograms and LSD technique. Fig. 3 consists of spectrograms of EMG and speech signals for the subjects Sp1, Sp2 and Sp3 for time t=0 and t=15 minutes. Normalized time is represented along x-axis where as normalized frequency is represented along y-axis. From EMG spectrograms, it can be observed that there is little difference between spectrograms at different time interval. The spectrograms become denser. But in case of speech spectrogram effect of fatigue can be observed more clearly. There is immense difference between the corresponding speech spectrograms on the bases of frequency. Due to fatigue, lower frequency component become more prominent while higher frequency component becomes diminished. For computing LSD, signal at t=0, of each subject was taken as the reference signal. Fig. 4 to Fig. 7 shows variation of LSD for EMG and speech signal w.r.t. time. In these figures x-axis shows time in minutes and y-axis shows magnitude of LSD. In Fig. 4 LSD variation of EMG is from 7.0 to 8.6 on the other hand LSD variation of speech signal is from 8.6 to 11.4. Fig. 5 LSD variation of EMG is from 8.1 to 8.6 on the other hand LSD variation of speech signal is from 8.2 to 10.3. Fig. 6 shows LSD variation of EMG is from 7.2 to 8.8 on the other hand LSD variation of speech signal is from 8.7 to 10.9. Fig. 7 LSD variation of EMG is from 7.7 to 8.4 on the other hand LSD variation of speech signal is from 7.8 to 9.1.

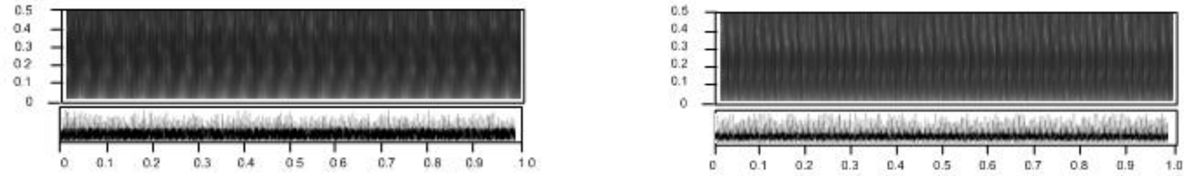
TABLE I. Karl person coefficient of correlation between time and signals

Subjects	EMG	Speech
Sp1	0.86	0.89
Sp2	0.82	0.81
Sp3	0.71	0.92
Sp4	0.61	0.96
Sp5	0.79	0.86
Sp6	0.67	0.88

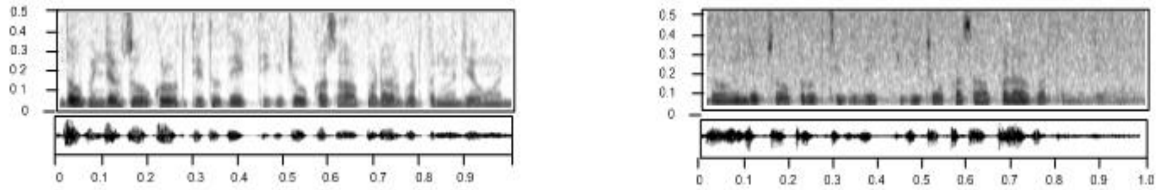
Karl person coefficient of correlation is calculated to find relation between different variables. The positive values in the Table I show that as the time progress due to fatigue, LSD value also increases. Karl person coefficient of correlation between duration of signals and time of signals is shows in Table II. Negative coefficients means duration of signal is inversely propositional to time of signals. So it can be understood that due to fatigue the duration of pronunciation of sentence decreases. Although there is increase in LSD value of speech and EMG signals, but in case of speech the increasing pattern is clearer than EMG.

Jang Bahadur Singh, Sandeep Arya, and Parveen Kumar Lehana, "Effect of fatigue on speech and EMG signals generated in zygomaticus muscles," *International Journal of Scientific and Technical Advancements*, Volume 2, Issue 4, pp. 49-52, 2016.

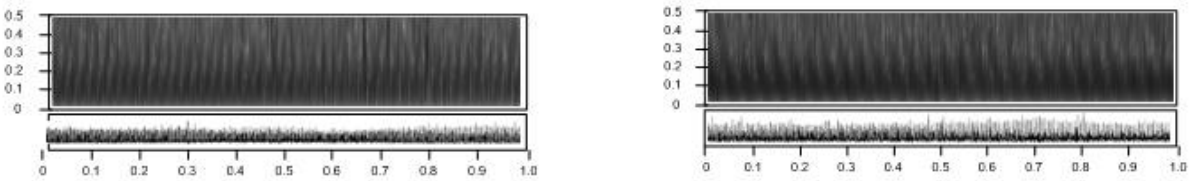
Signals at t=0 Signals at t=15 minutes



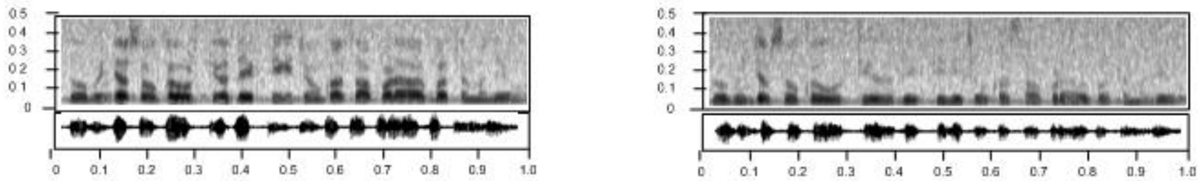
a) EMG for Sp1.



b) Speech for Sp1.



c) EMG for Sp2



d) Speech for Sp2.

Fig. 3. Spectrograms for EMG and speech signals for subjects Sp1 and Sp2 at time t=0 and t=15 minutes.

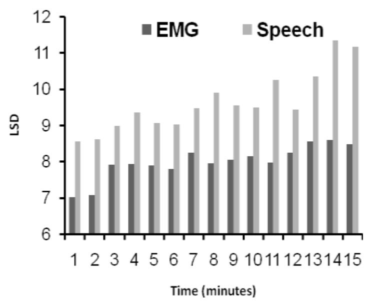


Fig. 4. Variations of LSD w. r. t time for EMG and speech signal for subject Sp1.

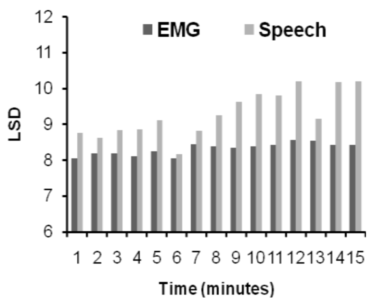


Fig. 5. Variations of LSD w. r. t time for EMG and speech signal for subject Sp2.

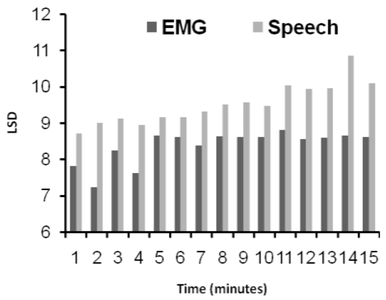


Fig. 6. Variations of LSD w. r. t time for EMG and speech signal for subject Sp3.

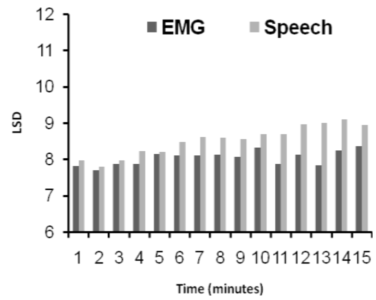


Fig. 7. Variations of LSD w. r. t time for EMG and speech signal for subject Sp4.

TABLE II. Karl person coefficient of correlation between length of signals and time.

Subjects	Coefficient Value
Sp1	-0.52
Sp2	-0.57
Sp3	-0.52
Sp4	-0.58
Sp5	-0.71
Sp6	-0.36

IV. Conclusion

Analysis has been carried out to study the effect of fatigue on speech and corresponding facial EMG signals at zygomaticus muscle. The analyses were done on the basis of spectrograms, LSD technique and Karl person coefficient of correlation. The experiment was conducted with six volunteer subjects. Effect of fatigue can be clearly observed on speech signals than EMG. As the time progress, due to fatigue LSD value increases and duration of sentence decreases. Also due to fatigue, lower frequency component become more prominent while higher frequency component becomes diminished.

References

[1] Krajewski, Jarek, Udo Trutschel, Martin Golz, David Sommer, and Dave Edwards. “Estimating fatigue from predetermined speech samples transmitted by operator communication systems.” In Driving Assessment Conference, Montana. 2009.

[2] Benzeghiba, Mohamed, Renato De Mori, Olivier Deroo, Stephane Dupont, Teodora Erbes, Denis Jouvet, Luciano Fissore et al. “Automatic speech recognition and speech variability: A review.” Speech Communication 49, no. 10 (2007): 763-786.

[3] Zhou, Guojun, John HL Hansen, and James F. Kaiser. “Nonlinear feature based classification of speech under stress.” IEEE Transactions on speech and audio processing 9, no. 3 (2001): 201-216.

[4] Bond, Zinny S., and Thomas J. Moore. A Note on Loud and Lombard Speech. OHIO UNIV ATHENS, 1990.

[5] Castellanos, Antonio, José-Miguel Benedí, and Francisco Casacuberta. “An analysis of general acoustic-phonetic features for Spanish speech produced with the Lombard effect.” Speech Communication 20, no. 1 (1996): 23-35.

[6] Murray, Iain R., John L. Arnott, and Elizabeth A. Rohwer. “Emotional stress in synthetic speech: Progress and future directions.” Speech Communication 20, no. 1 (1996): 85-91.

[7] Stanton, Bill J., L. H. Jamieson, and G. D. Allen. “Acoustic-phonetic analysis of loud and Lombard speech in simulated cockpit conditions.” In Acoustics, Speech, and Signal Processing, 1988. ICASSP-88., 1988 International Conference on, pp. 331-334. IEEE, 1988.

[8] Bou-Ghazale, Sahar E., and John HL Hansen. “Generating stressed speech from neutral speech using a modified CELP vocoder.” Speech Communication 20, no. 1 (1996): 93-110.

[9] Williams, Carl E., and Kenneth N. Stevens. “Emotions and speech: Some acoustical correlates.” The Journal of the Acoustical Society of America 52, no. 4B (1972): 1238-1250.

[10] Hansen, John HL. “Analysis and compensation of speech under stress and noise for environmental robustness in speech recognition.” Speech communication 20, no. 1 (1996): 151-173.

[11] Ozkaya, Ufuk, Ozlem Coskun, and Selcuk Comlekci. “Frequency analysis of EMG signals with Matlab sptool.” In Proceedings of the 9th WSEAS international conference on Signal processing, pp. 83-89. 2010.

[12] Farfán, Fernando D., Julio C. Politti, and Carmelo J. Felice. “Evaluation of EMG processing techniques using information theory.” Biomedical engineering online 9, no. 1 (2010): 72.

[13] T. Sharma, M. Kour, J. B. Singh, and P. Lehana, “Effect of Anger on EMG Signals Generated in Occipitofrontalis Muscle for Palatal Consonants.” International Journal of Advanced Research in Computer Science and Software Engineering, (2013): 1421.

[14] Edwards, Richard HT. “Human muscle function and fatigue.” Human muscle fatigue: physiological mechanisms (1981): 1-18.

[15] Baratta, R. V., M. Solomonow, B-H. Zhou, and M. Zhu. “Methods to reduce the variability of EMG power spectrum estimates.” Journal of Electromyography and Kinesiology 8, no. 5 (1998): 279-285.

[16] Bilodeau, Martin, A. Bertrand Arsenault, Denis Gravel, and Daniel Bourbonnais. “The influence of an increase in the level of force on the EMG power spectrum of elbow extensors.” European journal of applied physiology and occupational physiology 61, no. 5-6 (1990): 461-466.

[17] Laurent, Hélène, and Christian Doncarli. “Abrupt changes detection in the Time-Frequency Plane.” In Time-Frequency and Time-Scale Analysis, 1996. Proceedings of the IEEE-SP International Symposium on, pp. 285-288. IEEE, 1996.

[18] Karlsson, Stefan, Jun Yu, and Metin Akay. “Time-frequency analysis of myoelectric signals during dynamic contractions: a comparative study.” IEEE transactions on Biomedical Engineering 47, no. 2 (2000): 228-238.

[19] Bonato, Paolo, Serge H. Roy, Marco Knaflitz, and Carlo J. De Luca. “Time-frequency parameters of the surface myoelectric signal for assessing muscle fatigue during cyclic dynamic contractions.” IEEE Transactions on Biomedical Engineering 48, no. 7 (2001): 745-753.

[20] Lindstrom, Lars H., and Robert I. Magnusson. “Interpretation of myoelectric power spectra: a model and its applications.” Proceedings of the IEEE 65, no. 5 (1977): 653-662.

[21] Niu, Haijun, Ran Li, Guanglei Liu, Fang Pu, Deyu Li, and Yubo Fan. “Using EMG to Evaluate Muscular Fatigue Induced during Video Display Terminal Keyboard Use Task.” In 7th Asian-Pacific Conference on Medical and Biological Engineering, pp. 329-332. Springer Berlin Heidelberg, 2008.

Jang Bahadur Singh, Sandeep Arya, and Parveen Kumar Lehana, “Effect of fatigue on speech and EMG signals generated in zygomaticus muscles,” *International Journal of Scientific and Technical Advancements*, Volume 2, Issue 4, pp. 49-52, 2016.