Journal of Basic and Applied Engineering Research
Print ISSN: 2350-0077; Online ISSN: 2350-0255; Volume 2, Number 10; April-June, 2015 pp. 813-815

http://www.krishisanskriti.org/jbaer.html

# The Application of AR Coefficients and Burg Method in Sub-vocal EMG Pattern Recognition

**Munna Khan[1] and Mosarrat Jahan[2]**

*[1,2]Deptt. of Electrical Engineering Jamia Millia Islamia, New Delhi*
*E-mail: [1]mkhan4@jmi.ac.in, [2]mosarrat.jahan@gmail.comAbstract*

**Abstract—***This study shows the classification of the patterns for sub-vocal Hindi phonemes via electromyography (EMG) signals. Sub-vocal speech patterns are recognized by capturing the electric potentials of the human articulatory muscles that enables the user to communicate silently. The sub-vocal EMG recording was done on four channels BIOPAC System with MP30 Acquisition Unit. Four healthy subjects' students of our university with no known speech disorders, and whose native language is Hindi participated in the experiments. In the experimental recording sessions, the participants are silently spoken the Hindi phonemes. The EMG sensors are placed over the skin surface in the area of neck. In each experimental session, the EMG signals are taken corresponding to four examples of the Hindi phonemes (Ka, Kha, Ga, and Gha). The EMG signals have been collected from each subject using two pairs of self-adhesive Ag-AgCl electrodes. They are placed on surface of throat approximately 30 mm below the chin. The time series analysis, autoregressive (AR) coefficients and reflection coefficients serve for feature extraction. Burg algorithm has been employed for determination of AR coefficients. The Burg algorithm calculates the reflection coefficients such that forward and backward error minimizes. The reflection coefficients are independent of EMG signal amplitude and always lie between -1 and +1, so they do not require normalisation when used as features for classification. The classification performance of the above two feature sets is investigated for four classes Hindi phonemes (Ka, Kha, Ga, and Gha) using linear classifier. Confusion matrix is used to evaluate the performance of the classifier. Results showed that mean recognition rate of the reflection coefficients is superior to that of the AR coefficients. The recognition rate may vary according to various aspects, namely correct placement of the electrodes, sensitivity of system acquisition, signal conditioning, and feature extraction.*

## 1. INTRODUCTION

The area of research based on Sub-auditory speech recognition has short history. In 2003, [1] presented sub-acoustic speech recognition based on EMG signal for six sub-vocally words and 92% classification accuracy is achieved. In [2] showed that sub-vocal electromyogram (EMG) signal classification is used to control a modified web browser interface. An alternative way of communication being considered at NASA Ames Research Centre is the direct interpretation of nervous system control signals sent to speech muscles [3]. Chan et al. [4] present automatic speech recognition accuracy for EMG signals recorded from three speaking modes: vocalized, mouthed, and mentally rehearsed on the locations of the face and neck. Hidden Markov Model (HMM) based recognition system was trained for 65 word vocabulary produced by 9 American English Speakers in all three speaking modes. They found higher recognition accuracy 92% for the vocalized mode and 86% for mouthed speaking modes, but they are unable to conduct recognition on mentally rehearsed speech due to a lack of sufficient EMG activity.

This paper presents our recent research on Sub-vocal speech recognition based on surface electromyography (EMG), where electrical signals are captured from the (surface of throat) area of neck by means of surface electrodes. EMG recording for the sub-vocal Hindi phonemes is recorded on four channels BIOPAC system with MP30 acquisition unit. EMG signals are non-stationary in nature, therefore it cannot be analysed easily. Burg algorithm is used to compute the AR coefficients and reflection coefficients of the signal and is able to represent the signal successfully.

## 2. EXPERIMENTAL PROTOCOL AND DATA ACQUISITION

Four healthy subjects' students of our university with no known speech disorders, and whose native language is Hindi participated in the experiments. The EMG signals have been collected from each subject using two pairs of self-adhesive Ag-AgCl electrodes. Before placing the electrode, subject's skin is cleaned with alcohol wetted swabs. Conductive electrode gel is added to the electrodes to minimize the impedance at the skin-electrode surface contact. EMG signals for sub-vocal Hindi phonemes are recorded on four channels BIOPAC System with MP30 Acquisition Unit. In the experimental recording sessions, the participants were asked to sit on a chair and the Ag-Agcl sensors were placed over the skin surface in the area of neck as shown in Fig. 1. In each experimental session, the EMG signals are taken in correspondance to four examples of each of the Hindi phonemes (Ka, Kha, Ga, Gha). Each session is divided in 10 trials (the inter-trial time is 30 seconds). In a silent room, the subject reads Hindi phonemes Ka, Kh, Ga, Gha in sub-vocal speech. The sample rate of EMG signal is 500 samples/second.

**Fig. 1: Recording system.**

## 3. MATERIALS AND METHODS

Before feature extraction the acquired EMG signal can be further processed. The extracted signal is filtered using the Infinite Impulse Response (IIR) band-pass filter with the frequency bandwidth of 50-150 Hz. EMG data sets are modeled by AR model with model order 10. AR model is an all pole model where each sample of the signal can be expressed as a combination of previous samples weighted by constant coefficients and an error term. Value of current sample x(n) in a data sequence x(1), x(2) … , x(N) can be predicted as a linearly weighted sum of 'm' most recent sample values x(n-1), x(n-2), … x(n-m). This can be expressed as follows:

$$x(n) = \sum_{i=1}^{m} w_m(i)\, x(n-i) + \varepsilon(n) \qquad (1)$$

Where 'm' is model order and $w_m(i)$ is i$^{th}$ coefficient of the m$^{th}$ model order and $\varepsilon(n)$ is the white noise.

Burg algorithm calculates reflection coefficient so that they minimize the sum of forward and backward errors. Burg method ensures a stable AR model and is computationally efficient. This method results in high frequency resolution and is computationally efficient and is considered preferable for applications which require model of high accuracy.

EMG signal for sub-vocal phonemes "Ka" as shown in Fig. 2. Y axis represents magnitude in milli volt and X axis represents time in second and their burg spectral density is shown in Fig. 3 for model order 10.. AR coefficients and reflection coefficients used as features that represent relevant information in compact and meaningful form which can be further used as the basis of classifying the signal for pattern recognition. The feature vector is applied to the input of the classifier and the output score is calculated by following equation.

$$y = f(\vec{w}.\vec{x}) = f\left(\textstyle\sum_j w_j\, x_j\right) \qquad (2)$$

Where $\vec{w}$ is a weight vector, $x$ is the input vector, and $f$ is a function that converts the dot product of the two vectors into the desire output.

Performance of the classifier is evaluated by confusion matrix.

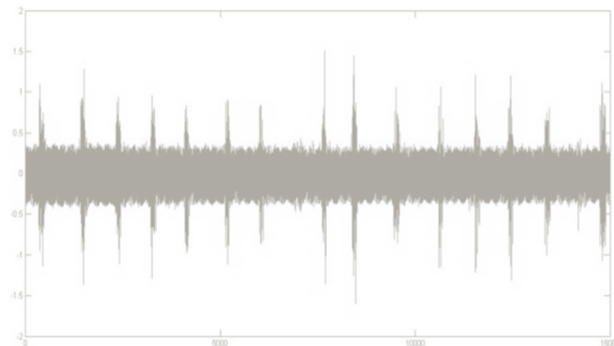

**Fig. 2: Sub-vocal EMG signal for 'Ka'**

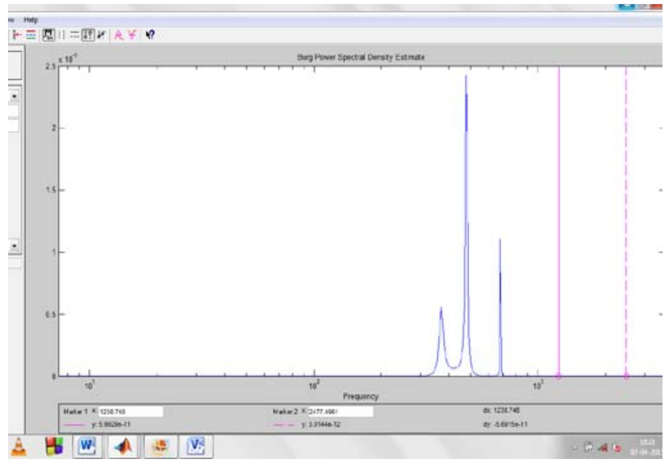


**Fig. 3: Burg spectral density for 'Ka'**

## 4. RESULT

We performed recording of two channel EMG signals for sub-vocal Hindi phonemes [Ka, Kha,Ga, and, Gha]. The acquired signals are processed through time domain analysis. AR coefficients and Reflection coefficients are estimated by Burg algorithm as features tabulated in Table 1 to 4. Absolute values of the extracted features are applied as input of the linear classifier for pattern recognition.

**Table 1: AC and RC for Ka**

| AC_ch1 | AC _ch2 | RC _ch1 | RC _ch2 |
|---|---|---|---|
| -0.113251 | -0.07867 | -0.364025 | -0.258923 |
| 0.504678 | 0.281043 | 0.258444 | 0.087582 |
| 0.230505 | 0.294729 | 0.1453159 | 0.202137 |
| 0.554687 | 0.592498 | 0.321864 | 0.407556 |
| 0.157015 | -0.040944 | 0.079572 | -0.111697 |
| 0.518531 | 0.485769 | 0.42030 | 0.440283 |
| 0.231613 | 0.286534 | 0.183843 | 0.257067 |
| 0.264716 | 0.194071 | 0.278688 | 0.181404 |
| 0.212155 | 0.121513 | 0.218979 | 0.131338 |
| 0.054513 | 0.106124 | 0.054513 | 0.106124 |

**Table 2: AC and RC for Kha**

| AC_ch1 | AC _ch2 | RC _ch1 | RC _ch2 |
|---|---|---|---|
| -0.105265 | -0.43613 | -0.49365 | -0.47630 |
| 0.435452 | 0.42378 | 0.218559 | 0.319185 |
| 0.240527 | 0.138237 | 0.272917 | 0.224343 |
| 0.598906 | 0.436994 | 0.434409 | 0.273847 |
| 0.089387 | -0.13674 | 0.075056 | -0.01012 |
| 0.565385 | 0.502490 | 0.538445 | 0.471839 |
| 0.225572 | 0.014259 | 0.225572 | 0.069621 |
| 0.280108 | 0.145183 | 0.309824 | 0.208787 |
| 0.176012 | 0.123260 | 0.175579 | 0.109331 |
| -0.00413 | -0.03219 | -0.00414 | -0.03219 |

**Table 3: AC and RC for Ga**

| AC_ch1 | AC _ch2 | RC _ch1 | RC _ch2 |
|---|---|---|---|
| -0.207 | 0.0118 | -0.4067 | -0.2797 |
| 0.5292 | 0.25720 | 0.3295 | 0.0556 |
| 0.1994 | 0.33364 | 0.1353 | 0.2112 |
| 0.5274 | 0.64726 | 0.29298 | 0.4585 |
| 0.1391 | 0.0705 | 0.08518 | -0.0556 |
| 0.4717 | 0.44065 | 0.3758 | 0.3863 |
| 0.22030 | 0.36532 | 0.1891 | 0.3275 |
| 0.24938 | 0.23771 | 0.2599 | 0.2166 |
| 0.18374 | 0.14548 | 0.2043 | 0.1460 |
| 0.0910 | 0.11306 | 0.09102 | 0.1130 |

**Table 4:AC and RC for Gha**

| AC_ch1 | AC _ch2 | RC _ch1 | RC _ch2 |
|---|---|---|---|
| -0.21533 | -0.191 | -0.3645 | -0.321 |
| 0.57654 | 0.3119 | 0.3339 | 0.1408 |
| 0.13814 | 0.2498 | 0.0857 | 0.2234 |
| 0.52552 | 0.5540 | 0.2762 | 0.3686 |
| 0.10603 | -0.1168 | 0.0974 | -0.1242 |
| 0.51872 | 0.5060 | 0.3894 | 0.4894 |
| 0.14580 | 0.2096 | 0.1284 | 0.2089 |
| 0.28207 | 0.1755 | 0.28938 | 0.1830 |
| 0.16292 | 0.1059 | 0.1808 | 0.1180 |
| 0.07829 | 0.0608 | 0.0782 | 0.0608 |

Confusion matrix evaluates the performance of the classifier. The result of the experiment showed that the average classification accuracy for sub-vocal EMG pattern recognition is 80 % for the features used as reflection coefficients (RC) and 75.5% for AR coefficients (AC). As the result is shown in Fig. 5 indicate that the proposed features are suitable for sub-vocal EMG classification and thus it can be used in real time for rehabilitative application.

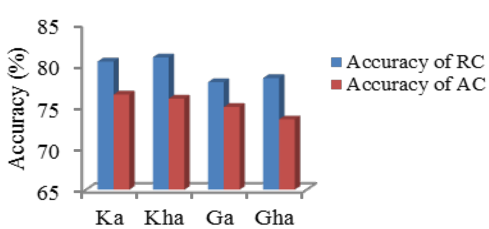


**Fig. 4: Classification accuracy (%)**

## 5. DISCUSSION

In this paper, we have studied burg algorithm techniques for EMG spectral analysis. We have used reflection coefficients and AR coefficients as features of sub-vocal EMG signal. The model selection criterion for AR model is based on reflection coefficients. Basically, our interest is more focused on the pattern recognition of sub-vocal phonemes. The test results indicated that the proposed technique is highly suitable for pattern recognition of sub-vocal phonemes and thus can be used to develop the real time module.

In future, we must optimize feature extraction transformation and classifier to reduce error levels, reduce sensitivity to signal noise and electrode locations and handle changes in the physiological states of the users.

## REFERENCES

[1] Jorgensen, C., Diana, D. L., and Shane, A., "Sub auditory speech Recognition Based on EMG/EPG signals", *NASA Ames Research Centre under the CICT/ITSR program*, January 25, 2003.

[2] Jorgensen, C., and Kim B., "Web Browser Control Using EMG Based Sub Vocal Speech Recognition ", *Proceedings of the 38th Hawaii International Conference on System Sciences* - 2005.

[3] Bradley, J. B., Kim B., and Jorgensen, C., "Small-vocabulary Speech recognition using surface electromyogrphy", *Science Direct*, October 2006.

[4] Chan, A.D.C., Engleheart, C., Engleheart, K., and, Lopvely, B., "Hidden Markov Model Classification of myoelectric signal in speech", *23rd Annual International Conference of IEEE Engineering in Medicine and Biology Society*, 2001.

[5] Rudoy, D., and Patrick, J. W., "Time-Varying Autoregressions in Speech: Detection Theory and Applications", *IEEE Transactions on audio, Speech, and Language processing*, May 2011.

[6] Michael, W., Szu-Chen, J., and Toth, R., "Impact of Different speaking mode on EMG-based Speech recognition", *ISCA* 2009.

[7] Cheng-Ning, H., Chun-Han, C., Hung-Yuan, C., "The Review of Applications and Measurements in Facial Electromyography", Journal *of Medical and Biological Engineering*, November 2004 pp. 15-20.

[8] Jonathan, S., Brumberg, A. N-C., Philip, R. K., Frank, H. G., "Brain–computer interfaces for speech communication", *Speech Communication 52*, *Elsevier*, January 2010, pp.367–379.

[9] Ahsan, Md. R., Ibrahimy, M.I. and Khalifa, O., "EMG Signal Classification for Human Computer Interaction: Review", *European Journal of Scientific Research*, 2009, pp.480-501.

[10] Panagiotis, K. A., "An EMG-Based Robot Control Scheme Robust to Time-Varying EMG Signal Features", *IEEE Transactions on Information Technology in Biomedicine*, May 2010.

[11] Stijn de, W., and Piet, M. T. B., "The Burg Algorithm for Segments", *IEEE Transactions on Signal Processing*, October 2000, pp. 2876-2880.

[12] Cinthia, I., "Epoch Length and Autoregressive-Order Selection for Electromyography Signals", *34th Annual International Conference of the IEEE EMBS San Diego*, California USA, 28 August - 1 September 2012.

[13] Michael, W., Matthias, J., and Tanja S., "Tackling Speaking Mode Varieties in EMG-Based Speech Recognition", *IEEE Transactions on Biomedical Engineering*, October 2014, pp. 2515-2526.

[14] Hefftner, G., Walter, Z., and George, G. J., "The Electromyogram (EMG) as a Control Signal for Functional Neuromuscular Stimulation-Part I: Autoregressive Modeling as a Means of EMG Signature Discrimination", *IEEE Transactions on Biomedical Engineering*, April 1988, pp. 230-237.