31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Use of sEMG in identification of low level muscle activities: features based on ICA and Fractal dimension

Ganesh R Naik, *Member, IEEE*, Dinesh K Kumar, *Senior Member, IEEE* and Sridhar Arjunan, *Member, IEEE*

Abstract— **This paper has experimentally verified and compared features of sEMG (Surface Electromyogram) such as ICA (Independent Component Analysis) and Fractal Dimension (FD) for identification of low level forearm muscle activities. The fractal dimension was used as a feature as reported in the literature. The normalized feature values were used as training and testing vectors for an Artificial neural network (ANN), in order to reduce inter-experimental variations. The identification accuracy using FD of four channels sEMG was 58%, and increased to 96% when the signals are separated to their independent components using ICA.**

I. INTRODUCTION

Surface Electromyogram (sEMG) is the recording of the myoelectric activity from the surface of skeletal muscles. It is closely related to the size and activity of the muscle and a measure of the functional state of muscle fibres [1],[2] and is useful to estimate the strength of contraction of the muscle. Surface EMG classification has been widely applied to many applications such as rehabilitation, design of mechatronic systems for prosthesis, and human-robot interaction/communication. The focus of the ongoing research in this field is on how to enhance the sEMG recognition accuracy. Like other pattern recognition problems, sEMG classification challenges researchers with the same two issues: feature selection and classifier design.

To identify low level forearm movements and actions the relative muscle activity from the different muscles in the forearm has to be identified. For this purpose, sEMG needs to be recorded using multiple electrodes. However due to the close proximity of the different active muscles, each of these electrodes record muscle activity from different muscles, referred to as cross talk. In case of the forearm, this is always a problem, and this is further exaggerated when the muscle activity is weak like during maintained isometric gestures. Spectral and temporal overlap makes the use of conventional filtering quite useless. Another difficulty of such identification of movements at low level of contraction is the poor signal to noise ratio for sEMG recording when muscle activity is small.

To better represent the properties of sEMG signal, fractal dimension (FD) of sEMG has been proposed [3],[4],[5]. The FD represents the scale invariant non-linear property of the signal and is an index for describing the irregularity of a time series in place of the power law index. Gitter et al.[6] demonstrated that the fractal dimension of EMG signal is correlated with muscle force. Another representation of identifying low-level movements' deals with considering individual muscles as independent at the local level and this makes an argument for separating the signals using Independent Component Analysis (ICA). In the recent past, due to the easy availability of ICA tools, numbers of researchers have attempted to use ICA for this application.

Research reported in this paper has experimentally verified and compared various features such as using ICA, and Fractal dimension based sEMG for identification of low level forearm muscle activities. The results indicate that identification accuracy using FD of four channels sEMG is 58% and it increases to 96% when the signals are separated to their independent components using ICA.

Ganesh R Naik, Sridhar Arjunan and Dinesh K Kumar are with Faculty of Electrical and Computer Engineering, RMIT University Melbourne, GPO BOX 2476 V, Melbourne, Australia - 3001. ganesh.naik@rmit.edu.au

II. BACKGROUND

A. Fractal dimension of sEMG

Fractals refer to objects or signal patterns that exhibit self-similarity with scale relationship that is fractional. Fractal Dimension (FD) is a measure of the fractal properties of any self-similar fractal structure. FD is a global property of a system [7],[8]. FD is normally estimated from the logarithmic relationship of the change in length of the curve with the change in the measurement scale.

FD = log (number of self-similar pieces)/ log (magnification factor)

FD of a process measures its complexity, spatial extent or its space filling capacity and is related to shape and dimensionality of the process [6]. It is related to the source properties and is expected to remain unchanged at various scales. The concept of fractal can be applied to physiological processes that are self-similar over multiple scales in time. Work reported by Gupta et al [9] and Gitter et al [6] has demonstrated that sEMG is a fractal signal. Gitter et al [6] have reported that the FD of EMG signal correlates with muscle force. Gupta et al [9] reported that the FD could be used to characterize the sEMG signal. Hu et al [4] distinguished two different patterns of FD of sEMG signals under different loading conditions. Based on the above, the authors propose to use FD as a measure to identify the low-level finger and wrist flexions.

B. ICA for sEMG

The problem of Blind Source Separation (BSS) consists of finding 'independent' source signals from their observed mixtures without a priori knowledge on the actual mixing

978-1-4244-3296-7/09/$25.00 ©2009 IEEE

channels. A common assumption in ICA-based methods is that the sources have a particular statistical behavior, such that the sources are random stationary statistically independent signals. Using this assumption, ICA attempts to linearly recombine the measured signals so as to achieve output signals that are as independent as possible [10],[11].

For linear mixing models, ICA is a valuable tool for BSS, and the mathematical formulation of the classical ICA is a simplified form of the BSS problem

$$x(t) = As(t) \tag{1}$$

where A is an $N \times M$ scalar matrix representing the unknown mixing coefficients and it is called transfer or mixing matrix. The goal of ICA is to find a linear transformation W of the dependent sensor signals $x(t)$ that makes the outputs as independent as possible:

$$\hat{s}(t) = Wx(t) = WAs(t) \tag{2}$$

where $s\hat{(t)}$ is an estimate of the sources. The sources are exactly recovered when W is the inverse of A up to a permutation and scale change [10],[12].

The sEMG signal is tested against the assumptions that underpin the theory of ICA. ICA is suitable for source separation when;

- The sources are statistically independent
- Independent components have non-Gaussian distribution
- The mixing matrix is invertible
- Sources and sensors are fixed
- Signal transmission delays are negligible

These assumptions are satisfied by sEMG because;

- Motor Unit Action Potentials (MUAPs) are statistically independent [13],[14],
- have non-Gaussian distributions,
- if the number of recordings is same as the number of sources, the mixing matrix will be square and invertible,
- the sources and electrodes are fixed and
- volume conduction in the tissue is essentially instantaneous [13],[14],[15].

Based on the above, ICA is suitable for separating sEMG recordings to obtain muscle activity if the number of channels is same as the number of active muscles.

III. METHODOLOGY

Experiments were conducted to evaluate the performance of the proposed ICA and Fractal based techniques. Surface EMG was recorded while the participant maintained isometric finger flexions.

A. sEMG Recording procedure

Experiments were conducted after obtaining approval from RMIT University human experiments ethics committee. Seven subjects, ages ranging from 21 to 32 years (five male subjects and two female subjects) volunteered for the experiments. sEMG was recorded using a Delsys eight channel sEMG acquisition system (Boston, MA, USA). Each channel has a pair of electrodes mounted together with a fixed inter-electrode distance of 10mm and a gain of 1000. Four electrode channels were placed over four different muscles as indicated in Table I and Fig. 1. A reference electrode was placed at Epicondylus Medialis.

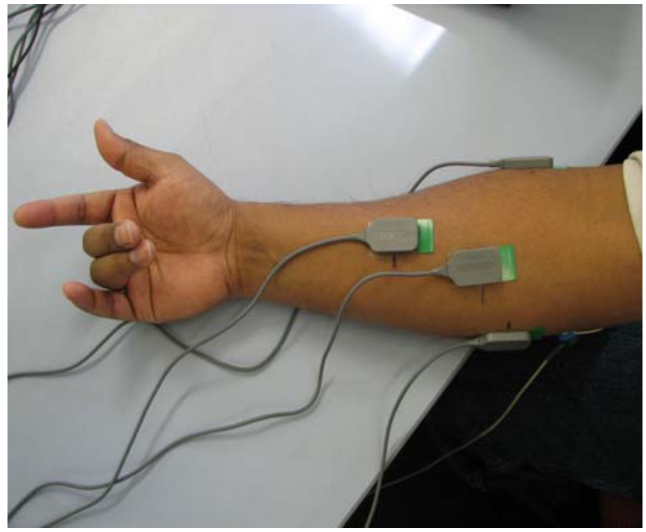

Fig. 1. Placement of electrodes for the experiments

TABLE I
MUSCLES USED IN THE EXPERIMENT

Channel	Muscles Involved
1	Brachioradialis
2	Flexor Carpi radialis (FCR)
3	Flexor Carpi Ulnaris (FCU)
4	Flexor digitorum superficialis (FDS)

The experiments were repeated on two different days. The forearm was resting on the table with elbow at an angle of approximately 90 degree and in a comfortable position. Four isometric finger flexions were performed and each was repeated 12 times each (Fig. 2, Table II), while the raw signal sampled at 1024 samples/second was recorded. Markers were used to obtain the isometric contraction signals during recording. A suitable resting time was given between each experiment. There was no external load. The actions were complex to determine the ability of the system when similar muscles were active simultaneously.

TABLE II
LIST OF FOUR WRIST AND FINGER FLEXION ACTIONS

Gestures	Actions
G1	All finger flexion
G2	Index and middle finger flexion
G3	Little and ring finger flexion
G4	Ring and middle finger flexion

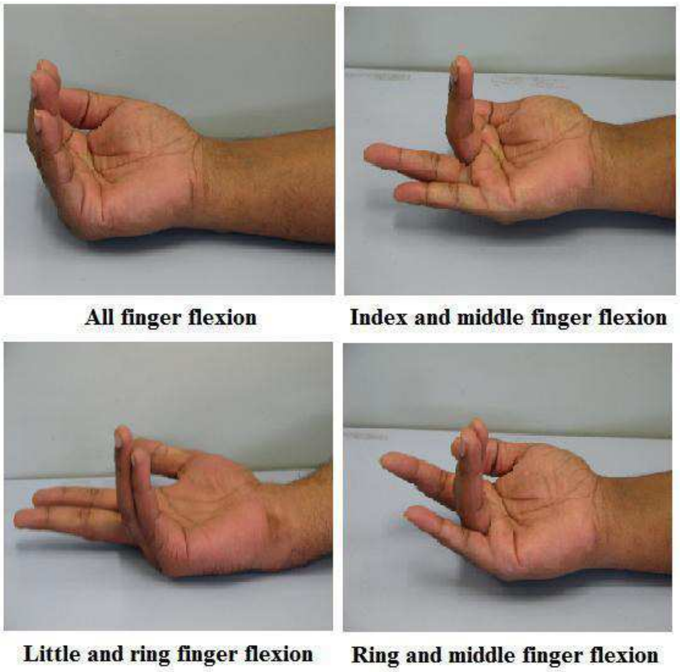

Fig. 2. Subtle finger flexions performed during the experiment

B. Data analysis

1) Computation of Fractal dimension of sEMG: The first step of the analysis required the computation of FD for each flexion data. Window size of 1024 samples or 1 second was used. Fractal dimension was calculated using Higuchi algorithm [16] for non-periodic and irregular time series. This algorithm yields a more accurate estimation of fractal dimension [17] for biosignals.

2) Calculation of Independent components of sEMG: For ICA analysis, sEMG was segmented to remove the start and end of each recording corresponding to the markers. FastICA algorithm [18] was then used to separate the four channels of sEMG using 4×4 matrix structures for the first day experiments. The estimated un-mixing matrix, W, was saved and corresponded to the participant. Root Mean Square (RMS) was computed for the four estimated separated signals to obtain one number corresponding to each muscle for each action. The above was repeated for each of the seven participants.

The un-mixing matrix, W, was then multiplied with the recordings of the experiments of the test data corresponding to the balance twenty experiments (not used for training). RMS was computed for each of the separated signals and this resulted in set of four RMS values for each experiment.

C. Classification of data

A neural network with four inputs, four outputs, and twenty hidden neurones was used to classify the data. Four RMS values of the muscles were the inputs and numbers identifying the four actions were the target. Data from four randomly selected experiments was used to train the network. The weight matrix obtained at the end of the training was saved to correspond to the participant. The training was repeated for each participant.

The system was tested using the data (not used for training) from the twenty experiments not used for training and for each participant. Similar to training, the input to the neural network was the set of normalized feature values of the sEMG signal using the un-mixing matrix corresponding to each participant. The weight matrix for each participant was used for the testing of the data of that participant. The output of the network was recorded and compared with the known corresponding actions and accuracy of identifying the action was estimated as a percentage. This was repeated for the seven participants.

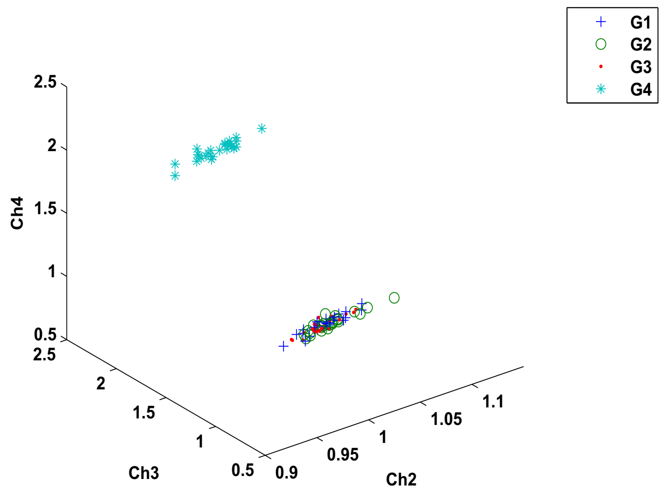

Fig. 3. Three dimensional plots showing the gesture (normalized data) classification using FD

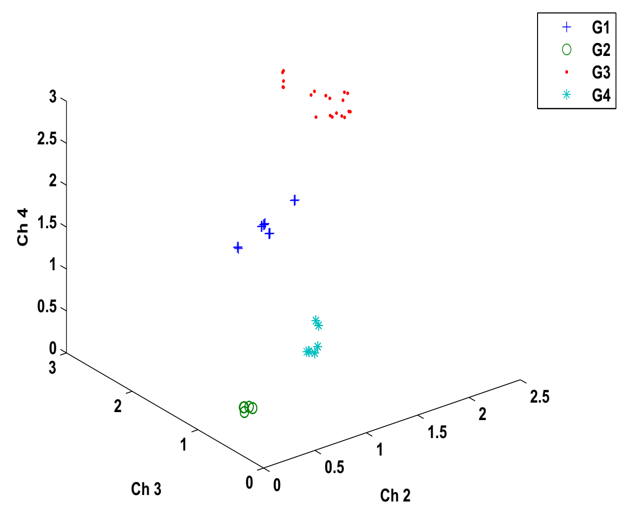

Fig. 4. Three dimensional plots showing the gesture (normalized data) classification using ICA

TABLE III

EXPERIMENTAL RESULTS FOR LOW LEVEL MUSCLE ACTIVITIES; FRACTAL DIMENSION AND ICA

	G1		G2		G3		G4	
Methods	Day One	Day Two	Day One	Day Two	Day One	Day Two	Day One	Day Two
FD	57.5%	58.5%	57%	59%	58.5%	57.5%	57.5%	58.5%
ICA	97%	96%	96%	97%	96.5%	95.5%	96.5%	96%

IV. Results and observations

A. Preliminary analysis

The features from four channel sEMG signal were normalized with respect to channel one in order to minimize the inter-experimental variations. To visualize the features, the data were plotted in three dimensional feature space. The plot shown in Fig. 3 demonstrates that there is no clear separation of different low - level forearm movements using FD. But the plot shown in Fig. 4 suggests that using ICA there is a clear indication of clusters for four different forearm movements.

The results of the experiments have been tabulated in Table III. From this table, it is observed that classification of sEMG after pre-processing using ICA with one un-mixing matrix and corresponding weight matrix for each individual, the identification accuracy for four isometric hand gestures is 96%. When fractal dimension was used as a measure the system accuracy is only 58%. The poor results of using FD is due to property remaining the same for all the forearm muscles considered during the low-level finger and wrist flexions.

V. Discussion and Conclusion

Experimental results demonstrate that classifying FD of sEMG (that has not been separated) to identify the finger and wrist flexion actions gives poor recognition of only 58%, the accuracy is better (96%) when the signal is separated using ICA. The poor accuracy in the use of FD is attributable to the property of the four forearm muscles remaining similar during activation, where there was no significant change in the fractal dimension for the isometric gestures.

The experiments have demonstrated that if ICA is used to separate the signal, there is the problem of order and scale ambiguity. To mitigate these shortcomings, the proposed system uses a set of un-mixing and weight matrices that separate and classify the signal. Because the ambiguities are the same during testing as during training, the test results indicate that the system accuracy is markedly better than the earlier techniques. While the results for sEMG using FD was only 58%, this method gives accuracy of 96% for the same set of recordings, and classified by very similar methods.

References

[1] J. Duchêne and F. Goubel, "Surface electromyogram during voluntary contraction: processing tools and relation to physiological events," *Crit Rev Biomed Eng*, vol. 21, no. 4, pp. 313–397, 1993.

[2] S. Karlsson, J. Yu, and M. Akay, "Time-frequency analysis of myoelectric signals during dynamic contractions: a comparative study," *Biomedical Engineering, IEEE Transactions on*, vol. 47, no. 2, pp. 228–238, 2000.

[3] C. J. Anmuth, G. Goldberg, and N. H. Mayer, "Fractal dimension of electromyographic signals recorded with surface electrodes during isometric contractions is linearly correlated with muscle activation," *Muscle & Nerve*, vol. 17, no. 8, pp. 953–954, 1994.

[4] X. Hu, Z. Wang, and X. Ren, "Classification of surface EMG signal with fractal dimension," *Journal of Zhejiang University Sciencen*, vol. 6B, no. 8, pp. 844–848, 2005.

[5] Z. Xu and S. Xiao, "Fractal dimension of surface EMG and its determinants," in *Engineering in Medicine and Biology Society, 1997. Proceedings of the 19th Annual International Conference of the IEEE*, vol. 4, 1997, pp. 1570–1573 vol.4.

[6] J. A. Gitter and M. J. Czerniecki, "Fractal analysis of the electromyographic interference pattern," *Journal of Neuroscience Methods*, pp. 103–108, May 1995.

[7] J. Theiler, "Estimating fractal dimension," *J. Opt. Soc. Am. A*, vol. 7, no. 6, pp. 1055+, June 1990.

[8] S. Suryanarayanan, V. Gupta, and N. P. Reddy, "Fractal analysis of surface EMG signals from the biceps," *International Journal of Medical Informatics*, pp. 185–192, July 1997.

[9] V. Gupta, S. Suryanarayanan, and N. P. Reddy, "Fractal dimension of surface EMG during isokinetic contractions," in *Engineering in Medicine and Biology Society, 1995., IEEE 17th Annual Conference*, vol. 2, 1995, pp. 1331–1332 vol.2.

[10] A. Hyvarinen, J. Karhunen, and E. Oja, *Independent Component Analysis*. Wiley-Interscience, May 2001.

[11] A. Hyvärinen, "Fast and robust fixed-point algorithms for independent component analysis," *IEEE Transactions on Neural Networks*, vol. 10, no. 3, pp. 626–634, 1999.

[12] A. J. Bell and T. J. Sejnowski, "An information-maximization approach to blind separation and blind deconvolution." *Neural Comput*, vol. 7, no. 6, pp. 1129–1159, November 1995.

[13] T.-P. Jung, C. Humphries, T.-W. Lee, S. Makeig, M. J. Mckeown, V. Iragui, and T. J. Sejnowski, "Extended ica removes artifacts from electroencephalographic recordings," in *NIPS '97: Proceedings of the 1997 conference on Advances in neural information processing systems 10*. MIT Press, 1998, pp. 894–900.

[14] M. J. Mckeown, S. Makeig, G. G. Brown, T.-P. Jung, S. S. Kindermann, A. J. Bell, and T. J. Sejnowski, "Analysis of fmri data by blind separation into independent spatial components," *Human Brain Mapping*, vol. 6, no. 3, pp. 160–188, 1998.

[15] T.-P. Jung, S. Makeig, M. Westerfield, J. Townsend, E. Courchesne, and T. Sejnowski, "Removal of eye activity artifacts from visual event-related potentials in normal and clinical subjects," *Clinical Neurophysiology*, vol. 111, October.

[16] T. Higuchi, "Approach to an irregular time series on the basis of the fractal theory," *Phys. D*, vol. 31, no. 2, pp. 277–283, June 1988.

[17] R. Esteller, G. Vachtsevanos, J. Echauz, and B. Litt, "A comparison of waveform fractal dimension algorithms," *Circuits and Systems I: Fundamental Theory and Applications, IEEE Transactions on*, vol. 48, no. 2, pp. 177–183, 2001.

[18] A. Hyvärinen and E. Oja, "A fast fixed-point algorithm for independent component analysis," *Neural Computation*, vol. 9, no. 7, pp. 1483–1492, 1997.