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# Novel Hand Gesture Classification based on Empirical Fourier Decomposition of sEMG Signals*

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*Abstract*— **Major challenge in building models for stroke rehabilitation stems from the non stationarity of the EMG signals. In this work we present a methodology for improved classification of hand gestures using Empirical Fourier Decomposition (EFD). First we apply the EFD technique on a set of publicly available dataset and later we reduce the dimensionality to collect most significant components. Finally we extract features from these components and perform hand gesture classifications using different machine learning (ML) models.**

***Clinical Relevance*—Compared to the state-of-art Empirical Wavelet Transform (EWT), the EFD technique reduced the total significant components considerably. To capture 90% of information from original data, the EFD approach needed 5.96% and 23.21% less number of components compared to EWT approach for original and dimensionally reduced data sets respectively. The classification models using EFD components gave an average 3.4% accuracy improvement compared to that of EWT components.**

## I. INTRODUCTION

Many muscle computer interfaces like exoskeletons, bio robotics depend on the surface electromyography (sEMG) signals derived from the hand muscles [1]. Bio-potential signal analysis techniques are often limited by the non stationary nature of the sEMG signal collected, i.e. the signal at a given instance may not convey enough meaningful information. For deeper insights, sEMG signals need to be processed for further transformation, analysis and interpretation like Fourier transform (FT), discrete wavelet transform (DWT), integral wavelet transform (IWT) etc. The approach Empirical Wavelet Transform (EWT) decomposes signals using adaptive wavelets filter bank improving time-frequency response [2]. However, EWT faces a mode mixing problem, i.e. it can't perform well on signals which have closely spaced modes. In this work we present an efficient way of gesture classification using Empirical Fourier Decomposition (EFD) which address the problem of closely spaced modes, an inherent problem in hand gesture sEMG data. Section II & III of the paper presents proposed methodology and analysis of experimental results. Section IV concludes the paper with summary of findings and future scope of the work.

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## II. METHODS

In this Section, we described the methodology used for applying the EFD and performing the classification.

### A. Applying Empirical Fourier Decomposition

Signal Decomposition technique EFD involves a segmentation step to divide the Fourier spectrum of signal that is to be decomposed and a step to construct a zero phase filter bank. Compared to EWT method, the boundaries of the decomposed segments are determined using an argmin function to better address the closely spaced modes.

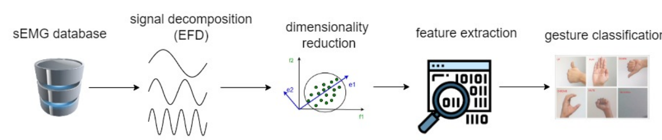


Fig. 1. Design flow of the proposed methodology

As shown in Fig. 1, we apply EFD on the sEMG data set. The multi-channel data sets are comprised of $i$ number of gestures $\{g_1, g_2, \ldots g_i\}$ each with $j$ number of trials $\{t_1, t_2, \ldots t_j\}$. Out of the total obtained components from decomposition, only a limited number of components are sufficient to extract the $\beta$ percentage of information of the undecomposed signal, $\beta$ can be 90%, 95% etc. In this work we aim to make gesture classification light weight using EFD by reducing the number of required components for representing $\beta$ percentage of signal. In the next step, the chosen components are dimensionally reduced using Principal Component Analysis (PCA) to make the data compact and yet retaining maximum information.

### B. Feature Extraction & Classification

For each of the signal component, we extracted various features like autoregression (ar), mean absolute value (mav), root mean square value (rms) and waveform length (wl). The feature values of components of each channel are clubbed together as a feature vector $fv_i$ as follows: $fv_1 = \{ar^1, ar^2, \ldots, ar^n\}$, $fv_2 = \{mav^1, mav^2, \ldots, mav^n\}$, $fv_3 = \{rms^1, rms^2, \ldots, rms^n\}$ and $fv_4 = \{wl^1, wl2, \ldots, wl^n\}$, where $n$ is the number of channels. These *fv*s are further used as by various machine learning models for gesture classification.

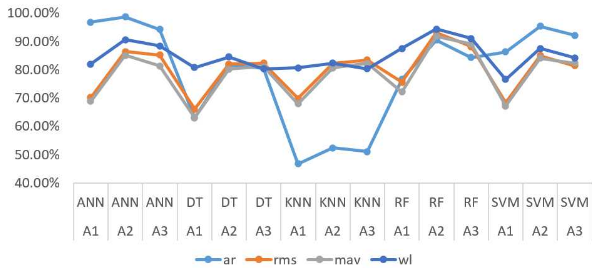


Fig. 2. Comparison of gesture classification accuracies for a random subject using various ML techniques. Effect of various features (ar, rms, mav, wl) are shown for three different approaches A1 (only PCA), A2 (EFD+PCA), A3 (EWT+PCA)

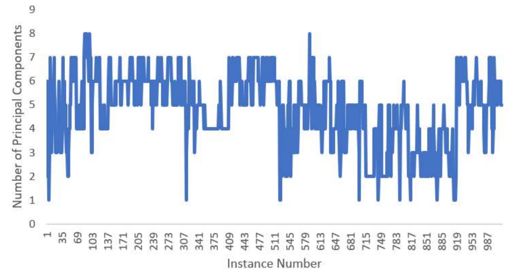


Fig. 3. Number of principal muscles (components) obtained for each of the 1020 instances

## III. Experimental Results

In this Section, we discuss the details of the experiments carried out to validate our EFD based gesture classification approach.

### A. DataSet

We used the publicly accessible NinaPro (DB2) [1], database to validate our approach. Database DB2 has 40 number of subjects. From these, 10 subjects were considered randomly to avoid any bias. All the 17 gestures corresponding to the finger and wrists movement for the 10 subjects were considered.

### B. Signal Decomposition and Comparison

EWT decomposition was applied, using the EWT function in Signal Processing Toolbox provided by MathWorks, while the algorithm and function of EFD is implemented by the Empirical Fourier Decomposition function Version 1.0 provided by author [3]. Both decomposition processing methods are conducted in MATLAB (R2021a). We used Python (Version 3.9.12) as the tool to implement PCA both on the components obtained from the EFD and EWT for each of the given trials of a particular gesture of a given subject. As can be seen in Fig. 3, the number of principal components for each of the 1020 (10 subjects X 17 gestures X 6 trails ) instances vary from 2 to 8 for 90% variance retention threshold. Resulting number of components from four different scenarios (two signal decomposition methods EWT, EFD and PCA applied on each) are listed in Table I. It can be clearly seen that EFD gave lesser number of components compared to EWT, both before and after PCA. This can be attributed to the fact that EFD handles the mode mixing problem in an efficient manner.

### C. Effect on Gesture Classification

For different approaches, various ML models ANN, RF, KNN, Decision Tree, SVM were deployed for classification of the obtained data with 80% -20% as training and testing sets. Corresponding gesture classification accuracies can be seen in Fig. 2. From the figure we can observe that applying signal decomposition in addition to only PCA (approach A1) based reduction gave improvement in accuracies in most of the machine learning models when rms, wl, mav used as features. Amongst the features, wl feature gave the most consistent result with superior accuracy. Amongst various ML models, ANN gave the best accuracy, reason can be ascertained to the fact that we are dealing with sufficiently large data sets which is the key advantage of ANN. Finally, it can be observed that approach A2 (i.e. EFD+PCA) performed better than approach A3 (i.e. EWT+PCA). An average (over different ML models) of 3.4% improvement in gesture classification accuracy compared to EWT approach is noted. This can be ascertained to the fact that the components obtained from EFD have no mode mixing problem which is predominant in EWT based decomposition. The fact that EFD approach achieved this improvement with significantly less number of components can be of great interest to system developers in stroke rehabilitation domain.

TABLE I

Signal Decomposition Comparison

| Method | number of components | Reduction compared to EWT |
|---|---|---|
| EWT | 58101 | - |
| EFD | 54636 | 5.96% |
| EWT + PCA | 23475 | - |
| EFD + PCA | 18025 | 23.21% |

## IV. Discussion & Conclusions

Empirical Fourier Decomposition based approach to classify hand gestures performed better than EWT approach due to its efficient handling of the mode mixing problem. EFD resulted in 23.21% lesser number of components and gave an average of 3.4% improvement in gesture classification accuracy. In future we would like to extend this work by identifying the key channels that are effective in gesture classification and validating on our own dataset.

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