# Fractional Integration Based Feature Extractor for EMG Signals

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***Abstract*—Electromyography (EMG) signals have been extensively used for identification of finger movements, hand gestures and physical activities. In the classification of EMG signals, the performance of the classifier is widely determined by the feature extraction methods. Thus, plenty of feature extraction methods based on time, histogram and frequency domain have been reported in literature. However, these methods have several drawbacks such as high time complexity, high computation demand and user supplied parameters. To overcome these deficiencies, in this work, a new feature extraction method has been proposed to classify EMG signals taken from two different datasets. While one of the datasets includes 14 different finger movements, the other consists of 20 different physical activities. The proposed method is based on numerical fractional integration of time series EMG signals with different fractional orders. K Nearest Neighborhood (KNN) classifier with 8-fold cross validation has been employed for prediction of EMG signals. The derived fractional features can give better results than the two commonly used time domain features, notably, mean absolute value (MAV) and waveform length (WL) in terms of accuracy. The experimental results are also supported with statistical analysis.**

***Index Terms*—Fractional integration, feature extraction, EMG, signal processing.**

## I. Introduction

Electromyography (EMG) signals are the measured bioelectrical signals that are generated by contraction of skeletal muscles during neuromuscular activities [1]. EMG signals have been widely used in broad scope of areas and applications such as diagnosis of some diseases [2], in the design of hand prosthesis [3]–[5] and entertainment industry [6]. With the advances of science, technology and speed of computers, EMG signals have become more important due to fact that they make people's life easier. Although the classification of hand gestures [1], [7]–[9] is most common in literature, the classification of finger movements [10], [11], movements of different body parts and body position [12] has been also researched.

The signal classification routine mainly consists of three parts including pre-processing, feature extraction and classification [6], [13]. In pre-processing step, so as to eliminate noises and interferences, the signals have been filtered firstly then, the windowing of datasets has been performed for the next step. On the other hand, in feature extraction step, the distinctive information based on time, frequency and/or time-frequency domains have been extracted. This step is very crucial owing to fact that it effects the performance of classifier, primarily. In the last step, the signals are classified by an appropriate classifier according to some feature sets. The prevailing classifiers are support vector machines (SVMs), decision trees (DTs), Naive Bayes (NB), K Nearest Neighborhood (KNN), neural networks (NNs), etc. [14], [15].

In order to classify the EMG signals, plenty of feature extraction methods have been reported in literature [6], [13], [15]–[17]. These methods can be split into three categories, namely, time domain, frequency domain and time-frequency domain (TFD). Since time domain features are calculated from the amplitudes of raw EMG data without any additional transformation, features in this category are fast and simple to compute. On the other hand, frequency domain features are usually based on statistical properties of power spectral destiny or spectrum of the EMG signals. They are usually employed for the muscle fatigue studies. Although TFD features may cause a good classification accuracy, they are very complex and time-consuming to compute. Moreover, they need to reduce their high dimensions before the classification step. Feature extraction methods have shown variable performance for different problems. So, it is very complicated to say that which feature set is the best for a specific problem. Additionally, some of the available feature extraction methods have good classification accuracy but they are usually complex and high computational cost [16]. Therefore, the discovery of new accurate feature extraction methods is still ongoing research. So, the time domain fractional order integration based feature extractor has been proposed in this work.

Fractional calculus, which considers the differential and integral expressions of arbitrary order, has been gained increasing interest, recently. It can find applications in engineering, signal processing, control, biology and modeling [18]. In the field of signal processing, the fractional order derivative and integral operators are usually employed for filtering purpose [19]. By means of fractional derivative, the canceling of electrocardiogram (ECG) artifacts in surface EMG signals [20], the detection of P and T waves [21], the detection of R wave in ECG [22], zero phase filtering for ECG denoising [23] and heart rate detection [24] have been studied. On the other hand, by using fractional integral, zero phase filtering on ECG signal [25] and ECG signal denoising [26] have been investigated. Except usage of fractional derivative and integral operators, electroencephalography and EMG signals have been filtered by fractional order filters [27]–[29]. To the best of the authors' knowledge, there is no study about fractional integration based feature extraction method for EMG signals in the literature yet.

Fractional order integration is the integration of arbitrary order [30]. Even though there are various fractional order integral definitions, Caputo and Riemann-Liouville (R-L) types

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are prominent ones [31]. It should be mentioned this point that these definitions are viable for continues time analog signals. However, their numerical version are also available in literature [32], [33]. The numerical version of R-L fractional integral in [33] is exploited in this work. The well-known time domain features of EMG signals mean absolute value (MAV), zero crossing, slope sign changes, waveform length (WL), Willison amplitude, variance, skewness, kurtosis etc. have been broadly used [1]. However, a number of valuable studies have shown that some of these features are redundant while the features of MAV and WL are usually significant and distinctive in terms of classification performance [1], [6]. Since the introduced feature extraction method is based on time-domain, this method has been compared with MAV and WL features.

Observing the performance of the proposed extraction method clearly, two different EMG signal datasets are taken into consideration. One of the datasets has eight channel fourteen different finger movements [11], while the other dataset has twenty different physical activities. On the other hand, to classify the EMG signals, KNN classifier with 8-fold cross validation has been operated for twenty times.

This work is structured as four sections. In the first section, the main reason of this work is introduced. In the second section, feature extraction methods with the proposed one are considered. In the section three, experimental results are presented and discussed. In the last section, in the lights of experimental results, the conclusion and possible future works are given.


Fig. 1. Finger motions

## II. Method

In this section, three steps involving pre-processing, feature extraction and classification are performed, respectively.

### A. Datasets

The dataset 1 is provided by Khushaba et al. for safe driving. During car driving, the distracting motions such as tuning the radio, controlling the windows and answering the phone endanger drivers' lives. To tackle this problem, simple finger motions (FM) can be used to perform the aforementioned tasks. However, the classification of FM is not that easy. Fourteen different FM demonstrated in Fig. 1 are recorded from eight channel EMG apparatus that is connected to driver's right arm. The eight subjects are participated in the experience. On the other hand, the dataset 2 involves three male and one female subjects. Each subject performed ten normal and ten aggressive physical activities (PA) during sessions. Eight channel EMG signals are recorded from right and left arms as well as legs.

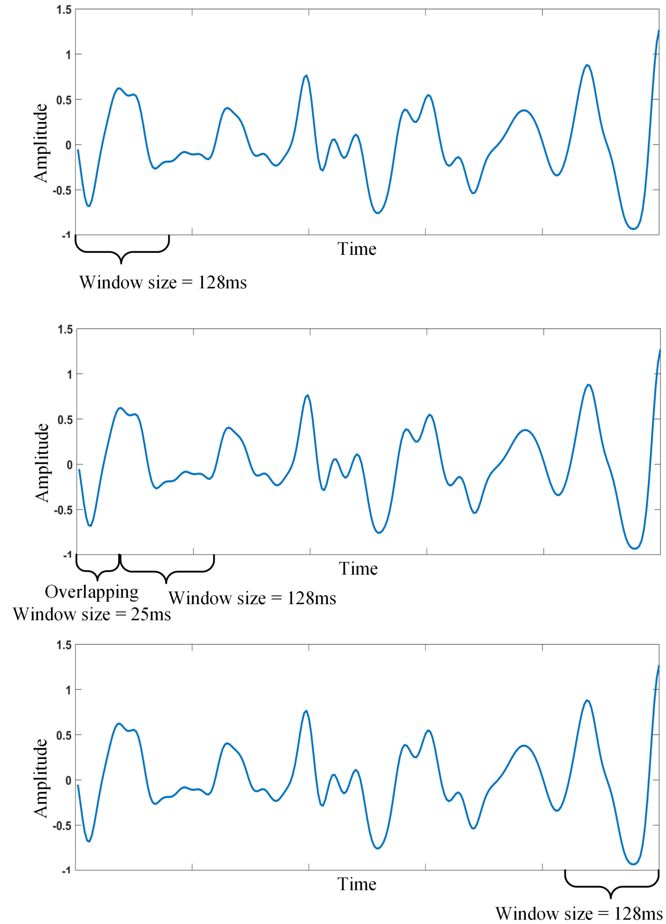


Fig. 2. Sliding windowing of data

### B. Pre-processing

Pre-processing is split into two steps. In the first step, raw EMG signals are denoised by means of the sixth order band-pass Butterworth filter with $20 - 450Hz$ bandwidth. Therefore, meaningful information is obtained. The second step is windowing of the filtered signals. To do this, a window of $128ms$ wide is sliding on the signals with a time step $25ms$ as shown in Fig. 2. Each window of $128ms$ wide is used for the feature extraction.

### C. Feature Extraction

High accuracy classification rate is achieved by effective feature extraction. For dataset 1, a typical signal part of $128ms$ window wide corresponds to 512 samples per channel due to sampling frequency $4kHz$. Totally, 4096 samples are available for eight channel. When whole signal length is considered, such a high sample can not be directly load the classifier. So feature extraction is a vital part of whole signal processing process. On the other hand, for a dataset 2, 331 samples per channel and totally 2648 samples are available. The features are numerical data that represents the original signal as good as possible. In this work, the following feature extraction methods are exploited owing to fast and easy computation.

*1) Mean Absolute Value (MAV):* MAV is the mean of the absolute values of the respective EMG signal amplitude. For EMG samples $x_k$ $(k = 1, 2, ...N)$, the mathematical expression of MAV is given as

$$MAV = \frac{1}{N}\sum_{k=1}^{N}|x_k| \tag{1}$$

where $N$ represents the total data points in a window.

*2) Waveform Length (WL):* WL is the sum of the amplitude differences between adjacent data points. It is the indicator of degree of amplitude change. WL is expessed as

$$WL = \sum_{k=1}^{N-1}|x_{k+1} - x_k| \tag{2}$$

where $x_k$ and $x_{k+1}$ are two adjacent data points of respective signal and $N$ is the sample size.

*3) The Proposed Feature Extraction Methods:* The proposed new feature extraction methods are based on fractional integration of arbitrary order. It is known that MAV and WL depend on integration of the integer order that is a special case of the fractional order. However, the fractional integration removes this limitation and provides extra freedom for researchers. The numerical version of R-L fractional integration is reported in [33] and computed in the interval $(0, T)$ as

$$I^{\alpha}x_N(h) = \frac{h^{\alpha}}{\Gamma(2+\alpha)}\sum_{n=0}^{N}c_{n,N}x_n \tag{3}$$

$$I^{\alpha}x(T) = I^{\alpha}x_N(h) + O(h^2) \tag{4}$$

where $\alpha > 0$ is fractional order, $h = T/N$ is time step, $N$ is total data points $\Gamma(.)$ is Gamma function, $x_{n,N}$ is respective signal, $O(h^2)$ is error term and $c_{n,N}$ is quadrature weights that is defined as below.

$$c_{n,N} = \left\{\begin{matrix} (1+\alpha)N^{\alpha} - N^{\alpha+1} + (N-1)^{\alpha+1} & if\ n=0 \\ (N-n+1)^{\alpha+1} - 2(N-n)^{\alpha+1} + (N-n-1)^{\alpha+1} & if\ 0<n<N \\ 1 & if\ n=N \end{matrix}\right\} \tag{5}$$

*4) Fractional Absolute Value (FAV):* FAV is the fractional integration of the absolute values of EMG signal points. Fractional integration order range from 0.1 to 1.5. The general expression of FAV is given below.

$$FAV = I^{\alpha}|x_k| \tag{6}$$

If (6) is inserted into (3), the following equation is derived as

$$FAV = \frac{h^{\alpha}}{\Gamma(2+\alpha)}\sum_{k=0}^{N}c_{k,N}|x_k| \tag{7}$$

where $x_k$ $(k = 0, 1, ...N)$ is EMG signal amplitude at the $k^{th}$ point.

*5) Fractional Waveform Length (FWL):* FWL is the fractional integration of the amplitude differences between adjacent data points of EMG signal. Fractional integration order range from 0.1 to 1.5. The general expression of FWL is given below.

$$FWL = I^{\alpha}|x_{k+1} - x_k| \tag{8}$$

By inserting (8) into (3), the following equation is derived as

$$FWL = \frac{h^{\alpha}}{\Gamma(2+\alpha)}\sum_{k=0}^{N}c_{k,N}|x_{k+1} - x_k| \tag{9}$$

## III. Results and Discussions

Extensive experiments on two public EMG data sets are conducted on a PC with an Intel I7 $4GHz$ processor with $16GB$ of RAM to verify the effectiveness and efficiency of the proposed methods, including FAV and FWL. The performance of the proposed methods are investigated for the different fractional orders.The accuracy value, which is obtained by using KNN classification method, is used as a performance metric for all simulations conducted in this study. The simulations are conducted by using two different data sets and are repeated 20 times with 8-cross validation technique for all fractional orders related to proposed methods and traditional methods including MAV and WL.

### A. Comparison of the classification performance of the proposed method with respect to fractional order

In this section, we show how to select the fractional order ($FO$) for EMG data sets in FAV and FWL schemes. Since, the maximum possible accuracy value of the proposed method may vary between different fractional order values. For this reason, the results on each data set for each prosed method are presented in Fig. 3 and 4 for better visual clarity.

The Fig. 3 and 4 show that the changing accuracy values of the proposed methods FAV and FWL with respect to fractional order for the FM and PA data sets, respectively. The accuracy rates are demonstrated in Fig. 3 for FM dataset where the average accuracy rates raised from $36.45\%$ to $97.59\%$ with changing $FO = 0.1$ to 1.07. $FO = 0.1$ score the lowest accuracy rate of $36.45\%$, while $FO = 1.04$ and 1.07 produce the highest accuracy rate of $97.59\%$. On the other hand in Fig. 4 we observe the lowest accuracy rate $46.4\%$ with $FO = 0.1$ and the highest one $97.99\%$ with $FO = 1.07$ for FAV method in PA data set. Also, it seen that from the same figure proposed method FWL has the worst and best performance for $FO = 0.1$ and $FO = 1.06$, respectively.

The results in Fig. 3 and 4 show that the classification accuracy of the proposed method for all four cases always yields the smallest classification performance between $FO = 0.1$ and $FO = 1.01$. The accuracy of proposed method is observed to

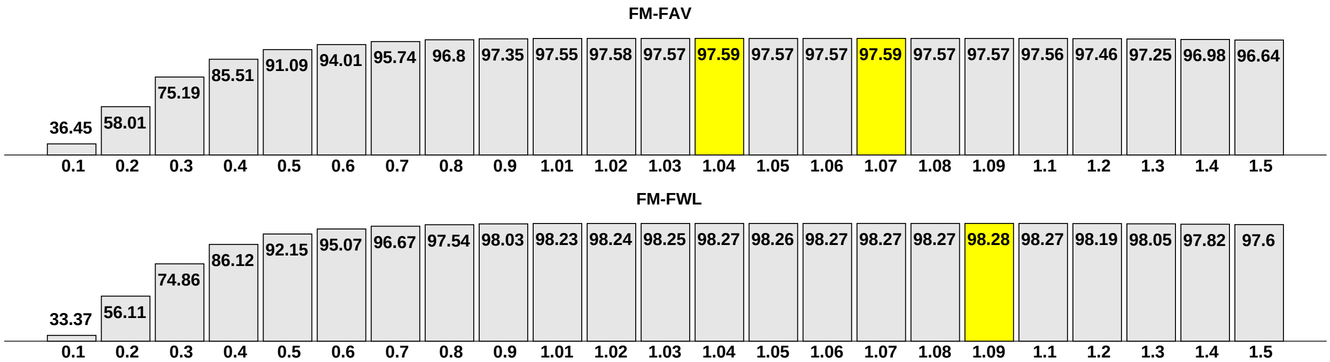


Fig. 3. The changing accuracy values of the proposed methods FAV and FWL with respect to the FO for the FM data set.

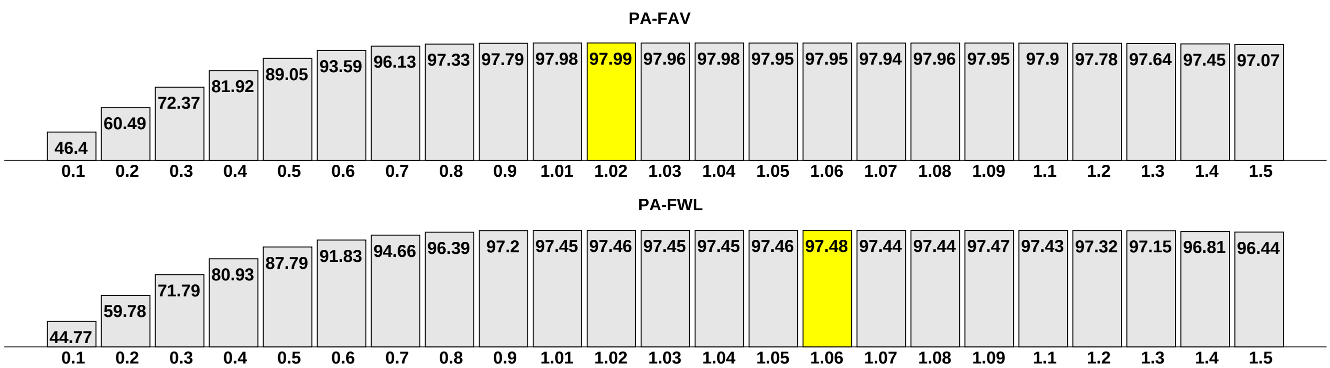


Fig. 4. The changing accuracy values of the proposed methods FAV and FWL with respect to the FO for the PA data set.

increase often monotonically with increasing the $FO$ values up to a point where its location between $FO = 1.01$ and $FO = 1.1$ and its best performance is attained in this range. In simulation, we observe that the typical ranges of appropriate $FO$ parameter do not usually vary dramatically for two EMG sets and adjusting this parameter to values within the interval $FO\epsilon[1.01, 1.1]$

To better assess how accuracies change according to each simulation, we represent results in Fig. 5, 6, 7 and 8 for the nine best $FO$ values. The results for the FM data set are presented in Fig. 5 and 6 with red and black color, along with the result of the conventional methods MAV and WL with blue color, for comparison. The proposed methods performance are better than conventional methods. Particularly proposed methods FAV and FWL exhibit the best classification performance for $FO = 1.04$ and $FO = 1.09$ with red color, respectively for FM data set. In the other data set PA, when comparing the proposed methods FAV and FWL to conventional methods MAV and WL, the proposed methods FAV with $FO = 1.02$ and FWL with $FO = 1.06$ has the best accuracy for each of these measures.

Some detailed descriptive statistical values, including, maximum (max), minimum (min), mean and standard deviation (std) are illustrated in Table I, II, III and IV for FM data set with FAV, FWL methods and PA data set with FAV, FWL methods, respectively. The results for the proposed FAV ($FO = 1.04$) at FM data set given in Table I where its accuracy rate are higher than conventional method MAV. Regarding another proposed method FWL ($FO = 1.09$) at the same data set, it can be seen from Table II its classification performance is better than the conventional method WL. In the case of FM data set, the results are listed in Table III and Table IV where the best accuracies values are FAV ($FO = 1.02$) and FWL ($FO = 1.06$), respectively.

The proposed feature extraction methods based on fractional integration are sufficient especially regarding the complexity of the classification of EMG signals in a practical application.

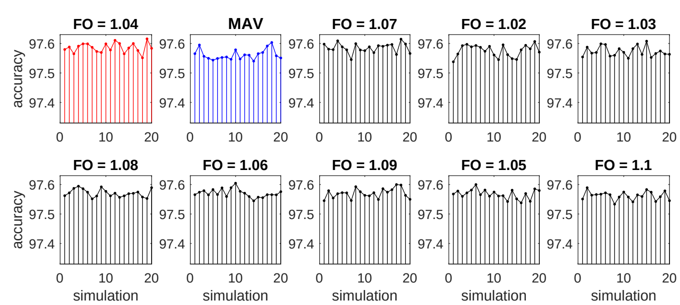


Fig. 5. Proposed method FAV performance throughout simulations for FM data set.

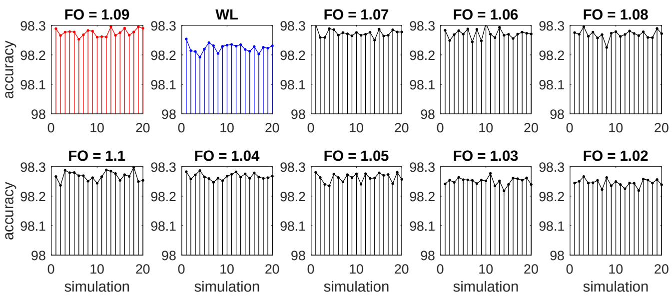


Fig. 6. Proposed method FWL performance throughout simulations for FM data set.

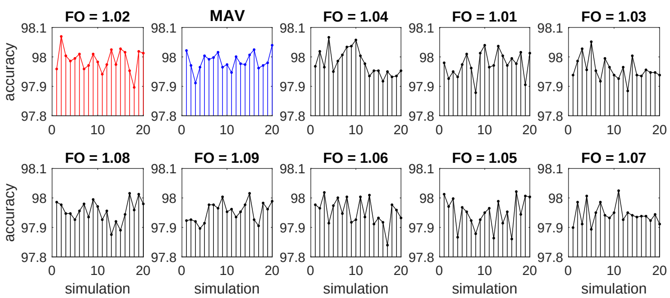


Fig. 7. Proposed method FAV performance throughout simulations for PA data set.

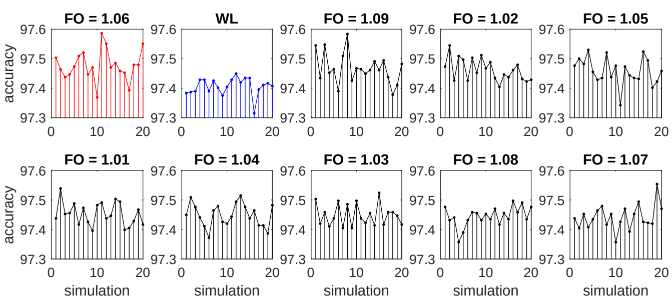


Fig. 8. Proposed method FWL performance throughout simulations for PA data set.

## B. Statistical analysis for the proposed method

In line of obtained results from the experimental study and basic descriptive statistical analysis, it should be note that proposed method has superior classification performance than the conventional approaches. However, in this section we validate obtained results by performing some additional statistical analysis. Since, we understand whether there is a sufficient difference between proposed method and conventional method or not. We have performed the Wilcoxon signed-rank test which is a non-parametric statistical test utilized to compare two repeated methods to assess whether two method is diffrent than each other. This test is an alternative to the paired t-test when the distribution of the differences between the two samples cannot be assumed to be normally distributed. A Wilcoxon signed-rank test is a nonparametric test, which utilized to determine whether two dependent samples are selected from populations having the same distribution.

The statistical results are listed in Table V and VI for FM and PA data sets. It can be seen that from Table V there is no statistical significance between the proposed method FAV with $FO = 1.04$ and its variants, including, FAV with $FO = 1.02$, 1.03, 1.06, 1.07, 1.08 and 1.09 in FM data set. On the other hand in favor of FAV with 1.04 we observe statistical significance between FAV with 1.04 and conventional technique MAV. In case of FWL with $FO = 1.09$, we observe nearly same results.

TABLE I
SOME DETAILED DESCRIPTIVE STATISTICAL VALUES, INCLUDING, MAX, MIN, MEAN AND STD FOR FAV AT FM DATA SET

| FM-FAV (1.04) | | | | |
|---|---|---|---|---|
| Method | Max | Mean | Min | std |
| FO: 0.1 | 36.5354 | 36.4508 | 36.3472 | 0.0537 |
| FO: 0.2 | 58.09 | 58.0064 | 57.9199 | 0.0506 |
| FO: 0.3 | 75.3074 | 75.1853 | 75.091 | 0.0478 |
| FO: 0.4 | 85.573 | 85.5058 | 85.4662 | 0.0281 |
| FO: 0.5 | 91.1336 | 91.089 | 91.0375 | 0.0252 |
| FO: 0.6 | 94.0518 | 94.0054 | 93.9647 | 0.0245 |
| FO: 0.7 | 95.7804 | 95.7436 | 95.7092 | 0.018 |
| FO: 0.8 | 96.8417 | 96.7994 | 96.7738 | 0.0168 |
| FO: 0.9 | 97.3904 | 97.35 | 97.318 | 0.0195 |
| FO: 1.01 | 97.5978 | 97.545 | 97.509 | 0.022 |
| FO: 1.02 | 97.6068 | 97.5758 | 97.5379 | 0.0203 |
| FO: 1.03 | 97.6079 | 97.5733 | 97.5497 | 0.0172 |
| **FO: 1.04** | **97.6158** | **97.5858** | **97.5514** | **0.0165** |
| FO: 1.05 | 97.6 | 97.5677 | 97.5379 | 0.0159 |
| FO: 1.06 | 97.6045 | 97.5705 | 97.5446 | 0.0138 |
| FO: 1.07 | 97.6147 | 97.5853 | 97.5452 | 0.0167 |
| FO: 1.08 | 97.5944 | 97.571 | 97.5514 | 0.0132 |
| FO: 1.09 | 97.6 | 97.5703 | 97.5452 | 0.0166 |
| FO: 1.1 | 97.5893 | 97.5623 | 97.5333 | 0.0146 |
| FO: 1.2 | 97.4876 | 97.4585 | 97.439 | 0.0122 |
| FO: 1.3 | 97.3011 | 97.2539 | 97.2152 | 0.0254 |
| FO: 1.4 | 97.027 | 96.9759 | 96.9439 | 0.0206 |
| FO: 1.5 | 96.6631 | 96.6393 | 96.6009 | 0.0195 |
| MAV | 97.6034 | 97.562 | 97.5401 | 0.0177 |

TABLE II
SOME DETAILED DESCRIPTIVE STATISTICAL VALUES, INCLUDING, MAX, MIN, MEAN AND STD FOR FWL AT FM DATA SET

| FM-FWL (1.09) | | | | |
|---|---|---|---|---|
| Method | Max | Mean | Min | std |
| FO: 0.1 | 33.4426 | 33.3686 | 33.2521 | 0.0466 |
| FO: 0.2 | 56.2048 | 56.115 | 56.042 | 0.0524 |
| FO: 0.3 | 74.9435 | 74.8614 | 74.7836 | 0.0478 |
| FO: 0.4 | 86.1737 | 86.1159 | 86.0432 | 0.0345 |
| FO: 0.5 | 92.2061 | 92.1516 | 92.088 | 0.0325 |
| FO: 0.6 | 95.1091 | 95.0726 | 95.0429 | 0.018 |
| FO: 0.7 | 96.6936 | 96.6652 | 96.6354 | 0.0167 |
| FO: 0.8 | 97.5627 | 97.5358 | 97.5113 | 0.0177 |
| FO: 0.9 | 98.0431 | 98.0253 | 98.0024 | 0.0111 |
| FO: 1.01 | 98.251 | 98.2305 | 98.1951 | 0.0134 |
| FO: 1.02 | 98.2663 | 98.2447 | 98.2188 | 0.0126 |
| FO: 1.03 | 98.277 | 98.2506 | 98.2177 | 0.0126 |
| FO: 1.04 | 98.2866 | 98.267 | 98.2465 | 0.0105 |
| FO: 1.05 | 98.2804 | 98.2627 | 98.2352 | 0.0146 |
| FO: 1.06 | 98.3064 | 98.2715 | 98.2442 | 0.0159 |
| FO: 1.07 | 98.303 | 98.2735 | 98.2499 | 0.0124 |
| FO: 1.08 | 98.2951 | 98.2695 | 98.225 | 0.0144 |
| **FO: 1.09** | **98.2957** | **98.2756** | **98.2527** | **0.0125** |
| FO: 1.1 | 98.2979 | 98.2676 | 98.2363 | 0.0163 |
| FO: 1.2 | 98.2177 | 98.1942 | 98.1736 | 0.014 |
| FO: 1.3 | 98.0736 | 98.0508 | 98.0182 | 0.0147 |
| FO: 1.4 | 97.8447 | 97.8217 | 97.7922 | 0.0168 |
| FO: 1.5 | 97.6368 | 97.5984 | 97.5712 | 0.0171 |
| WL | 98.2538 | 98.2235 | 98.1922 | 0.0144 |

TABLE III
SOME DETAILED DESCRIPTIVE STATISTICAL VALUES, INCLUDING, MAX, MIN, MEAN AND STD FOR FAV AT PA DATA SET

| PA-FAV (1.02) | | | | |
|---|---|---|---|---|
| Method | Max | Mean | Min | std |
| FO: 0.1 | 46.7181 | 46.4002 | 46.1878 | 0.1173 |
| FO: 0.2 | 60.6382 | 60.4873 | 60.3522 | 0.0852 |
| FO: 0.3 | 72.568 | 72.3661 | 72.1866 | 0.1107 |
| FO: 0.4 | 82.0397 | 81.9231 | 81.7627 | 0.0739 |
| FO: 0.5 | 89.1637 | 89.0464 | 88.9015 | 0.0709 |
| FO: 0.6 | 93.6627 | 93.5897 | 93.4601 | 0.0504 |
| FO: 0.7 | 96.1982 | 96.13 | 96.0343 | 0.0447 |
| FO: 0.8 | 97.387 | 97.3277 | 97.2231 | 0.0448 |
| FO: 0.9 | 97.8488 | 97.794 | 97.7386 | 0.0327 |
| FO: 1.01 | 98.0395 | 97.9759 | 97.8786 | 0.0424 |
| **FO: 1.02** | **98.0693** | **97.9892** | **97.8965** | **0.0378** |
| FO: 1.03 | 98.0514 | 97.9585 | 97.8846 | 0.0386 |
| FO: 1.04 | 98.0663 | 97.9799 | 97.9173 | 0.044 |
| FO: 1.05 | 98.0216 | 97.9485 | 97.8607 | 0.0513 |
| FO: 1.06 | 98.0187 | 97.9531 | 97.8399 | 0.0443 |
| FO: 1.07 | 98.0246 | 97.9445 | 97.8935 | 0.0338 |
| FO: 1.08 | 98.0157 | 97.955 | 97.8756 | 0.0366 |
| FO: 1.09 | 98.0157 | 97.9533 | 97.8965 | 0.0335 |
| FO: 1.1 | 97.9829 | 97.899 | 97.8429 | 0.0354 |
| FO: 1.2 | 97.8607 | 97.7825 | 97.7058 | 0.0457 |
| FO: 1.3 | 97.7088 | 97.6352 | 97.5807 | 0.0309 |
| FO: 1.4 | 97.5092 | 97.4506 | 97.393 | 0.0273 |
| FO: 1.5 | 97.1665 | 97.0683 | 96.9848 | 0.0523 |
| MAV | 98.0395 | 97.985 | 97.9114 | 0.0299 |

In case of PA data set, we observed statistically significant results among the different $FO$ values. However, there is no significance between proposed method FAV with $FO = 1.02$ and MAV methods. The possible reason of the this result is that conventional MAV has $FO = 1$, which is near to $FO = 1.02$. Besides, in favor of the proposed method FWL with $FO = 1.06$ it seen that there is statistically significance between FWL and conventional WL.

TABLE IV
SOME DETAILED DESCRIPTIVE STATISTICAL VALUES, INCLUDING, MAX, MIN, MEAN AND STD FOR WL AT PA DATA SET

| PA-FWL (1.06) | | | | |
|---|---|---|---|---|
| Method | Max | Mean | Min | std |
| FO: 0.1 | 44.9692 | 44.7651 | 44.5491 | 0.11 |
| FO: 0.2 | 60.0185 | 59.7835 | 59.6043 | 0.1097 |
| FO: 0.3 | 71.9632 | 71.7854 | 71.5639 | 0.0987 |
| FO: 0.4 | 81.0863 | 80.9338 | 80.7675 | 0.1012 |
| FO: 0.5 | 87.8795 | 87.7855 | 87.6263 | 0.0713 |
| FO: 0.6 | 91.9048 | 91.8278 | 91.6515 | 0.0597 |
| FO: 0.7 | 94.78 | 94.6557 | 94.5297 | 0.0602 |
| FO: 0.8 | 96.4634 | 96.3914 | 96.2935 | 0.0455 |
| FO: 0.9 | 97.2768 | 97.1978 | 97.1189 | 0.0472 |
| FO: 1.01 | 97.539 | 97.4528 | 97.3959 | 0.0389 |
| FO: 1.02 | 97.5449 | 97.4624 | 97.4049 | 0.0376 |
| FO: 1.03 | 97.5241 | 97.4485 | 97.4049 | 0.0365 |
| FO: 1.04 | 97.5151 | 97.4488 | 97.3721 | 0.0393 |
| FO: 1.05 | 97.53 | 97.4585 | 97.3423 | 0.0454 |
| **FO: 1.06** | **97.5866** | **97.4774** | **97.3691** | **0.0513** |
| FO: 1.07 | 97.5539 | 97.4418 | 97.3572 | 0.0419 |
| FO: 1.08 | 97.4972 | 97.4448 | 97.3572 | 0.0329 |
| FO: 1.09 | 97.5836 | 97.4676 | 97.3781 | 0.0517 |
| FO: 1.1 | 97.5568 | 97.4317 | 97.3572 | 0.056 |
| FO: 1.2 | 97.381 | 97.3164 | 97.2321 | 0.0441 |
| FO: 1.3 | 97.2261 | 97.1478 | 97.0861 | 0.0372 |
| FO: 1.4 | 96.8894 | 96.8062 | 96.7256 | 0.039 |
| FO: 1.5 | 96.517 | 96.4379 | 96.2995 | 0.0588 |
| WL | 97.4496 | 97.4065 | 97.3155 | 0.0294 |

TABLE V
STATISTICAL RESULTS FOR THE FM DATA SET

| Finger Movement Data Set | | | | | |
|---|---|---|---|---|---|
| MAV-FO: 1.04 | | | WL-FO: 1.09 | | |
| Method | p-val | Sig. | Method | p-val | Sig. |
| FO: 0.1 | 0 | FO: 1.04 | FO: 0.1 | 0 | FO: 1.09 |
| FO: 0.2 | 0 | FO: 1.04 | FO: 0.2 | 0 | FO: 1.09 |
| FO: 0.3 | 0 | FO: 1.04 | FO: 0.3 | 0 | FO: 1.09 |
| FO: 0.4 | 0 | FO: 1.04 | FO: 0.4 | 0 | FO: 1.09 |
| FO: 0.5 | 0 | FO: 1.04 | FO: 0.5 | 0 | FO: 1.09 |
| FO: 0.6 | 0 | FO: 1.04 | FO: 0.6 | 0 | FO: 1.09 |
| FO: 0.7 | 0 | FO: 1.04 | FO: 0.7 | 0 | FO: 1.09 |
| FO: 0.8 | 0 | FO: 1.04 | FO: 0.8 | 0 | FO: 1.09 |
| FO: 0.9 | 0 | FO: 1.04 | FO: 0.9 | 0 | FO: 1.09 |
| FO: 1.01 | 0 | FO: 1.04 | FO: 1.01 | 0 | FO: 1.09 |
| FO: 1.02 | 0.1367 | Nan | FO: 1.02 | 0 | FO: 1.09 |
| FO: 1.03 | 0.0166 | Nan | FO: 1.03 | 0 | FO: 1.09 |
| FO: 1.05 | 0.0025 | FO: 1.04 | FO: 1.04 | 0.0274 | FO: 1.09 |
| FO: 1.06 | 0.0055 | Nan | FO: 1.05 | 0.0123 | FO: 1.09 |
| FO: 1.07 | 0.8924 | Nan | FO: 1.06 | 0.4247 | Nan |
| FO: 1.08 | 0.0055 | Nan | FO: 1.07 | 0.4648 | Nan |
| FO: 1.09 | 0.0055 | Nan | FO: 1.08 | 0.2183 | Nan |
| FO: 1.1 | 0.0001 | FO: 1.04 | FO: 1.1 | 0.1554 | Nan |
| FO: 1.2 | 0 | FO: 1.04 | FO: 1.2 | 0 | FO: 1.09 |
| FO: 1.3 | 0 | FO: 1.04 | FO: 1.3 | 0 | FO: 1.09 |
| FO: 1.4 | 0 | FO: 1.04 | FO: 1.4 | 0 | FO: 1.09 |
| FO: 1.5 | 0 | FO: 1.04 | FO: 1.5 | 0 | FO: 1.09 |
| MAV | 0.0003 | FO: 1.04 | WL | 0 | FO: 1.09 |

TABLE VI
STATISTICAL RESULTS FOR THE PA DATA SET

| Physical Action Data Set | | | | | |
|---|---|---|---|---|---|
| MAV-FO: 1.02 | | | WL-FO: 1.06 | | |
| Method | p-val | Sig. | Method | p-val | Sig. |
| FO: 0.1 | 0 | FO: 1.02 | FO: 0.1 | 0 | FO: 1.06 |
| FO: 0.2 | 0 | FO: 1.02 | FO: 0.2 | 0 | FO: 1.06 |
| FO: 0.3 | 0 | FO: 1.02 | FO: 0.3 | 0 | FO: 1.06 |
| FO: 0.4 | 0 | FO: 1.02 | FO: 0.4 | 0 | FO: 1.06 |
| FO: 0.5 | 0 | FO: 1.02 | FO: 0.5 | 0 | FO: 1.06 |
| FO: 0.6 | 0 | FO: 1.02 | FO: 0.6 | 0 | FO: 1.06 |
| FO: 0.7 | 0 | FO: 1.02 | FO: 0.7 | 0 | FO: 1.06 |
| FO: 0.8 | 0 | FO: 1.02 | FO: 0.8 | 0 | FO: 1.06 |
| FO: 0.9 | 0 | FO: 1.02 | FO: 0.9 | 0 | FO: 1.06 |
| FO: 1.01 | 0.3716 | Nan | FO: 1.01 | 0.1134 | |
| FO: 1.03 | 0.0065 | FO: 1.02 | FO: 1.02 | 0.2232 | |
| FO: 1.04 | 0.2729 | Nan | FO: 1.03 | 0.0396 | FO: 1.06 |
| FO: 1.05 | 0.0094 | FO: 1.02 | FO: 1.04 | 0.0719 | FO: 1.06 |
| FO: 1.06 | 0.0105 | FO: 1.02 | FO: 1.05 | 0.2182 | |
| FO: 1.07 | 0.0004 | FO: 1.02 | FO: 1.07 | 0.0122 | FO: 1.06 |
| FO: 1.08 | 0.0065 | FO: 1.02 | FO: 1.08 | 0.0127 | FO: 1.06 |
| FO: 1.09 | 0.0053 | FO: 1.02 | FO: 1.09 | 0.3864 | |
| FO: 1.1 | 0 | FO: 1.02 | FO: 1.1 | 0.0109 | FO: 1.06 |
| FO: 1.2 | 0 | FO: 1.02 | FO: 1.2 | 0 | FO: 1.06 |
| FO: 1.3 | 0 | FO: 1.02 | FO: 1.3 | 0 | FO: 1.06 |
| FO: 1.4 | 0 | FO: 1.02 | FO: 1.4 | 0 | FO: 1.06 |
| FO: 1.5 | 0 | FO: 1.02 | FO: 1.5 | 0 | FO: 1.06 |
| MAV | 0.6649 | Nan | WL | 0 | FO: 1.06 |

In general, we can say that proposed method is statistically sufficient than the conventional methods. However proposed methods produce close results according to same $FO$ values ranging 1.02 and 1.09.

## IV. CONCLUSION

We proposed a new technique based on fractional integration to enhance the performance of a EMG feature extractors, including MAV and WL. The obtained results show that new MAV and WL, renamed as FAV and FWL, respectively can be used as sufficient feature extraction method. This method can be applied any feature extractor based on integration for further researches. Only limitation of the proposed method is that it is depend on an user supplied parameter fractional order. In order to solve this problem we performed number of simulations, which lead how to choose this value. On the other hand, the fractional derivative based feaure extraction method may be a candidate for the future studies.

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