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HD-sEMG Signal Denoising Method for Improved Classification Performance in Transhumeral Amputees Prosthesis Control

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***Abstract*- Surface myoelectric pattern recognition (sMPR) based control strategy is a popularly adopted scheme for multifunctional upper limb prostheses. Meanwhile, above-elbow amputees (transhumeral: TH) usually have limited residual arm muscles, that mostly hinder the provision of requisite signals necessary for physiologically appropriate sMPR control. Hence, the need to maximally explore the limited signals to realize adequate sMPR control scheme in practical settings. This study proposes an effective signal denoising method driven by *Multi-scale Local Polynomial Transform* (MLPT) concept that can improve the signal quality, thus allowing adequate decoding of TH amputees' motion intent from high-density electromyogram (HD-sEMG) signals. The proposed method's performance was systematically investigated with HD-sEMG signals obtained from TH amputees that performed multiple classes of targeted upper limb movement tasks, and compared with two common signal denoising methods based on wavelet transform. The obtained results show that the proposed MLPT method outperformed both existing methods for motion tasks decoding with over 13.0% increment in accuracy across subjects. The possibility of generating distinct and repeatable myoelectric contraction patterns using the MLPT based denoised HDs-EMG recordings was investigated. The obtained results proved that the MLPT method can better denoise and aid the reconstruction of myoelectric signal patterns of the amputees. Therefore, this suggest the potential of the MLPT method in characterizing high-level upper limb amputees' muscle activation patterns in the context of sMPR prostheses control scheme.**

I. INTRODUCTION

For decades, robotic devices driven by surface myoelectric pattern recognition (sMPR) control schemes for upper limb motor function rehabilitation and restoration have received widespread attention in the industry and academia [1]. The wide interest in sMPR control strategies is due to their non-invasiveness, relatively ease of acquisition, promotion of muscle tone, and provision of large amount of information about the user's motion compared to other biomedical signals [2]. In a typical sEMG-PR based prosthesis control scheme, users are expected to generate repeatable muscle contraction patterns when performing specific limb motion tasks. From such patterns, motor information encoded in their myoelectric signals are decoded and used to provide control commands for prosthetic device [3]. However, using conventional myoelectric recordings, individuals with high degree of limb loss (transhumeral amputees) are unable to generate the requisite signals for physiologically appropriate control, due to their limited residual arm muscles [4]. For this singular reason, high density surface electromyogram (HD-sEMG) technique has been considered a viable option for recording multi-site signals with closely spaced electrodes. Interestingly, HD-sEMG has been utilized to obtain tiny muscle activation patterns towards enhancing the accuracy of movement intention classification, which is beneficial for the control of the prosthesis. Also, HD-sEMG offers good temporal information that allows different muscle activation patterns to be captured [5-6]. Nevertheless, accurate decoding of motion intents in above elbow amputees is still a huge challenge because the signals are easily and often corrupted by interferences such as baseline wander (with non-linear and non-stationary characteristics), power-line noise, and white Gaussian noise among others. These interferences mainly affect the signal quality and amount of motor information available for amputees' motion intent decoding.

Signal denoising methods including wavelet denoising (WD) [7], filtering-based techniques [8], ensemble empirical mode decomposition [9], blind source seperation [10] and hybrid methods [11-12] have been proposed as solution to improve the quality of HD-sEMG recordings. Among these methods, WD based techniques have increasingly been explored. This is because WD provides multi-resolution time-frequency analysis and preserve signal characteristics while reducing inherent noises [7, 13]. In [14], wavelet analysis was utilized to evaluate the quality of sEMG recordings for class separability. Gradolewski et al. reported that WD is effective for denoising EMG signals upon selection of appropriate wavelet parameters [13]. Furthermore, hybrid methods that combined WT and independent component analysis [15], artificial neural network (NN) with WT [16] among others have been proposed towards achieving better denoising outcomes. In spite of the wide adoption of WD techniques, factors such as contamination of clean signal with visual artifacts, dependency on mother wavelet selection [17, 18], inability to combine smoothness with good numerical properties, computational complexity affect their denoising capabilities in practical applications, and this calls for further study [17]. In this regard, this study propose an extension of wavelet method based on multi-scale local polynomial

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transform (MLPT) to denoise HD-sEMG signals obtained from four transhumeral amputees. The proposed method adopts a statistical non-parametric estimation concept that operates based on repeatable local polynomial smoothing process and multi-scale decomposition. The performance of the proposed method was compared with the original signal (OD) and commonly applied wavelet-based denoising methods including Daubechies-4 (DB) and Coiflets-5 (COIF) using a decomposition level of 4. Also, considering the availability of limited muscle sites on residual arm of the transhumeral amputees, the possibility of obtaining distinct and repeatable patterns from the preprocessed HD-sEMG recordings using the proposed method was examined.

II. MATERIALS AND METHODS

A. Subject Information

In this study, four male subjects with transhumeral amputation (denoted as TransH1, TransH2, TransH3, TransH4) aged between 35-49 years with stump lengths of 20cm, 25cm, 27cm, and 30cm, respectively (measured from the scapula down to the length of the stump) were recruited [4]. All the amputees agreed to participate in the study after the research objective and the experimental process were carefully described to them. Thereafter, a consent form was signed by subjects indicating that their data can be used for publication towards promoting science, technology, and education. The entire study protocol was approved by the Institutional Review Board of Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences, China.

B. Instrumentation

A HD-sEMG system (REFA 128 model, TMS International, REFA, Oldenzaal, The Netherlands) was used for the signal acquisition. The REFA system electrode cables are protected to ensure that interferences such as cable motion artifacts and power interference are minimized.

C. Electrode Placement

A total of 32 monopolar electrodes were placed on the skin surface area of the stump arm of each subject to collect the sEMG signals (Figure 1a). In this study two different electrode configurations were adopted because of the length of the amputee's residual arm (The stump length of subjects TransH1 and TransH2 are relatively shorter than the other two subjects). For TransH1 and TransH2 , twenty electrodes were distributed in a 2x10 grid format around the biceps brachii and triceps muscles (Figure 1b) while the remaining twelve were placed on the deltoid muscle in a 3x4 grid format (Figure 1c). While for TransH3 and TransH4 subjects, all the 32 electrodes were placed on the biceps brachii and triceps muscles in a 4x8 grid format. Meanwhile, a reference electrode was placed on each subject's intact arm's wrist.

D. Signal Collection and Preprocessing

After setting up the HD-sEMG signal acquisition equipment and placing the electrodes on the residual arm of the subjects, five motion classes including hand open (HO), hand close (HC), wrist pronation (WP), wrist supination (WS), and no movement (NM) were introduced to the subjects. They were given enough time to practice the different motion classes. After being familiar with these classes, each subject was asked to perform each movement for 5 seconds and then rest for 5 seconds before observing the preceding motion class. A 5s rest period was given between each set of movement to avoid mental and muscle fatigue. In this experiment, each subject performed five repetitions of the motion classes, thereby producing 25s EMG recording per class. The recorded data were preprocessed offline using Matlab®2017b toolbox. (The Mathworks, Massachusetts). A 5[th] Order-Butterworth filter with frequency bands between 20 Hz (lower band) and 500 Hz (upper band) was applied to obtain the useful frequency range muscular activities while 50Hz notch filter was used to eliminate power line interference. Meanwhile, a sampling frequency of 1024Hz was utilized during the sEMG data collection. It is worth noting that these conventional filtering techniques were applied to the raw HD-sEMG signals before further preprocessing with the proposed and existing methods considered in this study.

Figure 1: (a) Experimental setup for the HD-sEMG recording and electrodes configuration on the (b) biceps brachii and triceps muscle and (c) deltoid muscle for TransH1 subject.

E. Proposed Multi-Scale Local Polynomial Transform Denoising Method

Towards improving the signal quality for adequate classification of above-elbow amputees' motion intent, a multi-scale local polynomial transform (MLPT) is proposed to denoise the HD-sEMG recordings. The MLPT method is implemented as a laplacian pyramid extension using lifting principle, where a kernel function smoothens fine-scale coefficients with a given bandwidth to obtain the coarser resolution coefficients of the signals [17]. Generally, the proposed MLPT denoising process is classified into three stages (including signal subsampling, prediction and update). A description of the approach is given as follows.

Suppose the HD-sEMG signal is represented as $f(x)$, observed in n covariate values $X_i \in [0,1]$ under additive noise. The covariate values are assumed to be ordered statistically in a random manner, expressed as:

$$((Y_i | X_{(i)} = x_i) = f(x_i) + \sigma Z_i \quad (1)$$

Also, assuming the noise is normal and independently distributed; the designed points fluctuate around equidistant grid (that is $E(X_{(i)}) = {}^{i}/_{n}$) and $f(x)$ is piecewise smooth, such that the MLPT takes the observation as fine input scale. Therefore, the multi-scale iteration is initialized by:

$$s_{j,k} = Y_{k+1} \; for \; k = 0, \ldots, n-1 \quad (2)$$

where j is the highest resolution level.

Similarly, let $n_j = n$ and $x_j = x$ which represent the length of s_j and the corresponding vector of the covariates, respectively. Then, the MLPT constructs successive approximations of s_j associated with a subsampled vector of x_j which is expressed as:

$$x_j = x_{j+1,e(j+1)} \quad (3)$$

Where x_{j+1} is a vector of length n_{j+1} at a resolution level labelled $j+1$.

The subsampling matrix denoted as $\tilde{J}_j$ is the $n_j \times n_{j+1}$ rectangular matrix obtained by taking all rows r from the $n_{j+1} \times n_{j+1}$ identity matrix for which $r \in e(j+1)$ such that:

$$x_j = \tilde{J}_j \, x_{j+1} \quad (4)$$

The subsampling matrix, $\tilde{J}_j$ can be replaced by a general $n_j \times n_{j+1}$ rectangular matrix $\tilde{F}_j$, that is:

$$s_j = \tilde{F}_j s_{j+1} \quad (5)$$

The purpose of the replacement was to reduce the variance in s_j. During the subsampling process, a detailed coefficient vector d_j (Equation 6) can be used to recover signal lost while the diagonal matrix (D_j^{-1},) is used for standardization.

$$d_j = D_j^{-1}\left(s_{j+1} - P_j s_j\right) \quad (6)$$

For the prediction of s_{j+1}, s_j is used for the construction and in most points of x_{j+1}, the predictions perform well, meaning that the offset vector $D_j d_j$ is sparse, containing many zeroes.

In this study, we adopted the MLPT where P_j is the local polynomial smoothing matrix which has its kth value $P_j(x_{j+1,k}; x_j)$ where $P_j(x;\, x_j)$ is a vector of length n_j with components depending on variable x, given by:

$$P_j(x;\, x_j) = X^{\tilde{p}}(x)\left(X_j^{(\tilde{p})^T} W_j(x) X_j^{(\tilde{p})}\right)^{-1} (X_j^{(\tilde{p})^T} W_j(x)) \quad (8)$$

where $X^{\tilde{p}}(x) = [1x, \ldots, x^{\tilde{p}-1}]$ is a row vector of $\tilde{p}$ power functions, the integer $\tilde{p}$ is the order of the prediction and $W_j(x)$ is the diagonal matrix of weights with its corresponding elements:

$$(W_j)_{kk}(x) = K\left(\frac{x - x_{j,k}}{h_j}\right) \quad (9)$$

The $K(x)$ is the kernel function and h_j is the bandwidth, user-controlled scale used at the resolution level j

F. Data Analysis

The acquired HD-sEMG recordings was denoised using the proposed and the considered denoising methods. Towards improving the performance and response time of the EMG control system, an overlapping technique with a window length of 150 ms and 100 ms increment was utilized to segment the preprocessed data into different analysis windows. Afterward, the commonly used Hudgins' four time-domain feature sets, including mean absolute value (MAV), number of zero crossings (ZC), waveform length (WL), and number of slope sign changes (SSC) [19], were extracted from each analysis window and Linear Discriminant Analysis (LDA) classifier was applied to classify the motion classes. Furthermore, paired sample t-test was utilized to examine the statistical significant between the proposed and existing methods with a confidence level set to $p<0.05$. The classifier was trained and tested using 5-fold cross validation while its performance was evaluated using classification accuracy (CA) and Matthew Correlation Coefficient (MCC) defined in Equation 10 and 11, respectively.

$$CA = \frac{correctly\ classified\ samples}{Total\ number\ of\ testing\ samples} * 100\% \quad (10)$$

$$MCC = \frac{(TP*TN) - (FP*FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (11)$$

where TP: true positives, TN: true negatives, FP : number of false positives, and FN: number of false negatives.

In addition, the study utilized an energy map to check whether repeatable muscle activation patterns across repetitions of a specific motion classes can be obtained from the MLPT based processed HD-sEMG recordings or not. This is because the subject's ability to perform unique and repeatable motion patterns is vital for realizing an effective sMPR control system. The energy map was created using the root mean square (RMS) of the signals based on the signal amplitude. It shows the muscle activity's shape and the region where the activity is detected on the residual arm during each motion class.

III. RESULT

A. Evaluation of Classification Performance

Table I shows the classification accuracies of the proposed method, notable existing denoising methods and the original signal across all the limb movements and subjects. From Table 1, it can be observed that the denoised signals obtained after applying the proposed method achieved better accuracies for individual class of limb movement task

Table I: Motion-wise classification accuracy for each subject using the four time domain features and LDA classifier

Subjects▶	***TransH1***				***TransH2***				***TransH3***				***TransH4***			
Classes▼	MLPT	DB	COIF	OS	MLPT	DB	COIF	OS	MLPT	DB	COIF	OS	MLPT	DB	COIF	OS
HC	91.85	81.02	85.16	77.39	98.89	89.87	89.53	82.54	98.43	65.94	64.77	63.98	97.67	75.41	80.56	74.57
HO	79.41	63.05	65.33	59.48	94.87	80.11	79.85	76.69	96.64	71.65	70.20	65.67	96.57	84.68	83.75	82.94
WP	91.01	82.74	83.97	80.70	98.78	88.24	84.39	75.20	96.66	83.48	82.24	83.41	97.24	88.32	87.50	83.00
WS	87.29	63.97	74.26	66.68	96.81	88.73	85.51	84.10	99.61	83.98	86.45	78.83	95.67	71.29	77.36	69.20
NM	96.10	82.04	84.36	82.73	99.62	78.66	85.58	85.16	99.59	88.23	87.27	83.40	96.93	92.87	92.20	89.30
Mean	**89.13**	74.56	78.62	73.40	**97.79**	85.12	84.97	80.74	**98.19**	78.66	78.19	75.06	**96.82**	82.51	84.27	79.80

Note: MLPT is the proposed method, DB is daubechies 4 wavelet, COIF denotes the Coiflets 5 wavelet and OS represents the original signal. Decomposition level of 4 was employed for DB and COIF compared to the existing denoising methods and the original signal. To be precise, the proposed method outperformed other methods with an increment in accuracy in the range of 10.51% - 23.13% across motion classes and subjects. The performance of the methods were also evaluated on individual subject's basis and the result is presented in Figure 2.

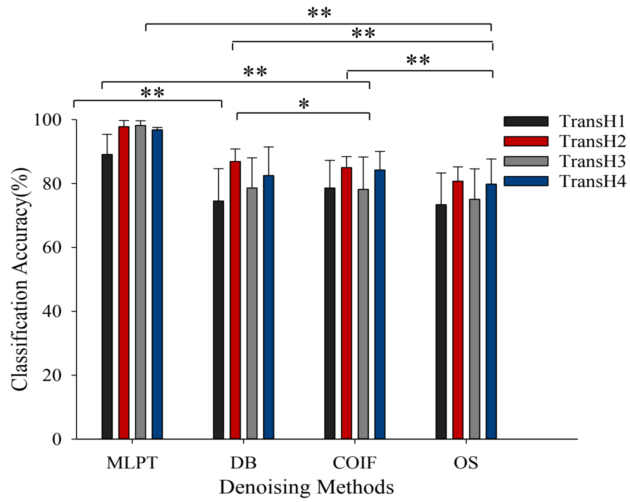

Figure 2: Average classification accuracy of each subject across movement classes for the proposed and existing methods. Note: ** and * means that the mean is statistically and not statistically significant, respectively.

From the obtained results, it can be deduced that the proposed method achieved the highest accuracy with a statistical significance difference at *p = 0.0037, p = 0.0067 and p = 0.0016* for DB, COIF and OS respectively. Meanwhile, as shown in Figure 2, there is a statistical significant difference between the original signal and existing methods (DB and COIF). At the same time, there is no significant difference between the performances of the existing methods. Examining the proposed method, existing methods, and original signal performances based on the individual subject, we found that TransH2 recorded the highest accuracy. In contrast, TransH1 (except for the COIF method) achieved the lowest accuracy. Similar performance trend was recorded when the MLPT was evaluated and compared with existing methods using the MCC metric. Across subjects and movement classes, the MLPT method, achieved the highest MCC of 0.97 compared to DB and COIF that recorded 0.84 and 0.83, correspondingly. It is worth noting that subsequent analysis focused on examining the performance of the MLPT method because it outperformed other methods as shown in the previous results.

B. Repeatability of Muscle Activation Pattern using RMS-Energy Maps based on the proposed MLPT method

In this section, we investigated the capability of the MLPT based denoised HD-sEMG signals in aiding the generation of distinct and repeatable muscle activation patterns, and the result is presented in Figure 3. Due to the number of page limitation, we considered reporting only the HO task of the TransH1 subject, and the associated RMS-Energy maps were constructed from channels 22 and 23 (selected randomly), located on the deltoid muscle region, as shown in Figure 3. Figure 3a-3c and Figure 3d-3f represent the energy map of three repetitions for channels 22 and 23 during the HO motion class. By closely observing Figure 3a-3c maps, muscle activity patterns across the three repetitions are relatively similar, although with little variability and slightly variant energy intensity. Also, a similar phenomenon was observed in Figure 3d-3f (channel 23). From this result, it can be deduced that the proposed method may aid the generation of distinct and repeatable muscle activation patterns across electrode channels.

C. Visualization of HD-sEMG Signal Denoising based on MLPT

Figure 4 represents the waveform estimation outcomes of the proposed MLPT method with respect to the original signal

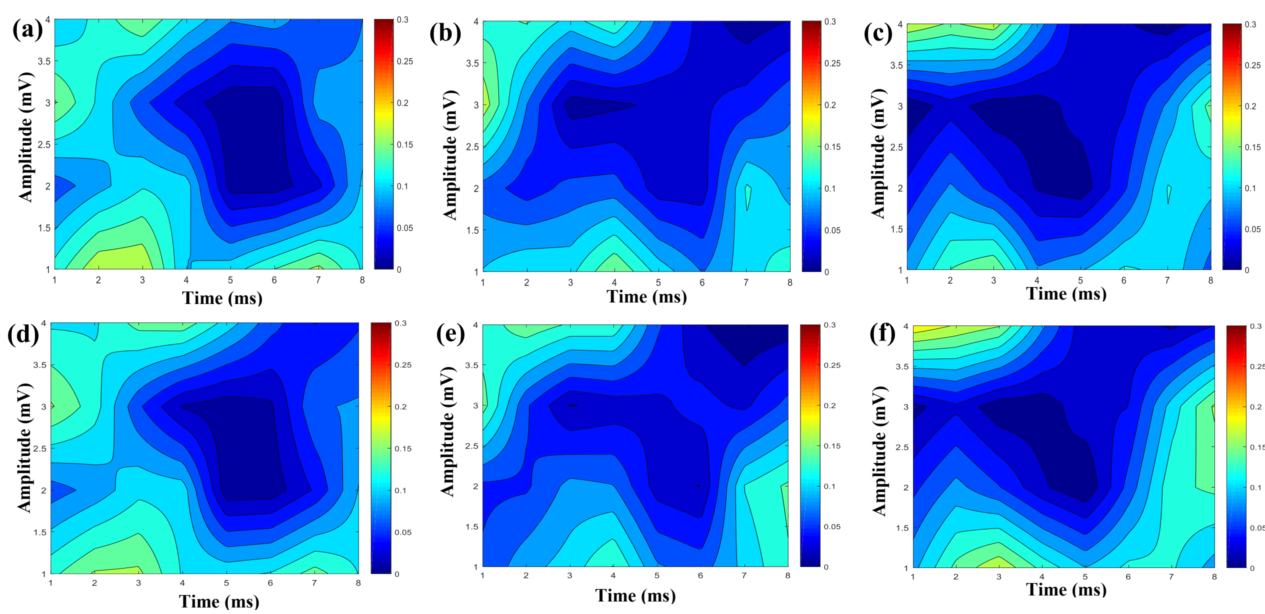

Figure 3: Visualization of RMS-Energy maps of sEMG activities in the residual arm of transhumeral amputee subject during three repetitions of hand open tasks (a-c) for channel- 22 and (d-f) for channel -23.

for the same hand open (HO) limb movement task in channel 22. It can be observed that the method was able to attenuate inherent noises (most especially the baseline noise) to a reasonable extent, and this allowed proper reconstruction and estimation of the original signal's characteristics as shown in Figure 4.

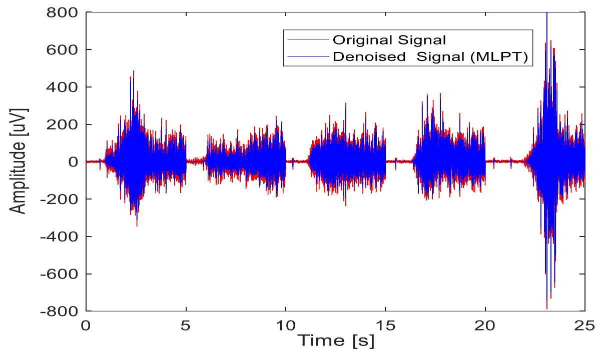

Figure 4: Signal estimation of channel 22, class hand open (HO)

Note that the signal in red denotes the original signal while the signal in blue color denotes the denoised and reconstructed version after applying the proposed method (MLPT). This signal estimation result support the performance of the proposed method recorded in the results reported in Table I and Figure 2. Thus, this further emphasizes the potential of the proposed method in characterizing high-level upper limb amputees' motion intents in the context of sMPR prostheses control strategy.

IV. CONCLUSION

In this study, a signal denoising method based on *Multi-Scale Local Polynomial Transform* is proposed towards enhancing the overall quality of HD-sEMG recordings from transhumeral amputee subjects. Afterward, we examined whether the MLPT based denoised signals can effectively aid the generation of distinct and repeatability of muscle activation patterns across repetition of motion classes since it is essential towards realizing an intuitive and accurate EMG-PR control system. From the experimental results, the proposed method achieved significantly higher classification performance with an overall average accuracy of 95.48±2.33% across subjects and motion classes. Notably, an accuracy of above 95% has rarely been reported for transhumeral amputees in decoding their movement intent from sEMG signals to the best of our knowledge, which suggests the proposed method's efficacy compared to the existing methods. Also it can be deduced from the energy map results that few repeatable muscle activation patterns can be achieved and probably be sufficient to provide stable and high movement intent decoding outcomes for subjects with above elbow amputation. It is noteworthy that further investigations will be carried out in our future work to further validate findings from this work. Also, we will examine the computational complexity and classification performance of the proposed and existing denoising methods using different decomposition levels.

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