Biomedical Signal Processing and Control 71 (2022) 103153

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Novel finger movement classification method based on multi-centered binary pattern using surface electromyogram signals

Turker Tuncer [a], Sengul Dogan [a], Abdulhamit Subasi [b,c,*]

[a] Department of Digital Forensics Engineering, College of Technology, Firat University, Elazig, Turkey
[b] Institute of Biomedicine, Faculty of Medicine, University of Turku, 20520 Turku, Finland
[c] Department of Computer Science, College of Engineering, Effat University, Jeddah 21478, Saudi Arabia

ARTICLE INFO

Keywords:
Multi-centered binary pattern (MCBP)
Surface electromyogram (sEMG)
Finger movements classification
Machine learning

ABSTRACT

The number of individuals who have lost their fingers in our world is quite high and these individuals experience great difficulties in performing their daily work. Finger movements classification and prediction are one of the hot-topic research areas for biomedical engineering, machine learning and computer sciences. This study purposes finger movements classification and prediction. For this purpose, a novel finger movements classification method is presented by using surface electromyogram (sEMG) signals. To accurately classify these movements, a novel binary pattern like textural feature extractor is presented and this textural micro pattern is called as multi-centered binary pattern (MCBP). In the MCBP, five odd-indexed values of a block are utilized as center. The proposed MCBP based multileveled finger movements classification method evaluate by three cases. In the first case, the raw sEMG signals are utilized as input. In the second and third case, sEMG signals are divided into frames and these frames are utilized as input. A two-layered feature selector is used to choose the most valuable features. The purpose of using these two feature selectors together is to choose the optimum number of features. In the classification phase, two fine-tuned classifiers have been used and they are k-nearest neighbor (k-NN) and support vector machine (SVM). The proposed MCBP based method achieved 99.17%, 99.70% and 99.62% classification rates using SVM classifier according to Case 1, Case 2 and Case3 respectively. The results show that the study is a highly accurate method.

1. Introduction

Individuals with human forearm loss have great difficulty performing their daily activities. These individuals with upper limb amputation are too much to ignore in the world. These individuals have difficulty in real life activities [1,2]. Individuals need some prosthetic devices to perform their daily activities completely [3,4]. These prosthetic devices are a tool used for individuals to perform the movements experiencing disruption. Prosthetic devices can be controlled with signals called surface electromyograms (sEMG) [5,6]. EMG signals are generally defined as the electrical activity that occurs in muscle contraction and stagnant states. EMG is used to diagnose various muscle related diseases, follow the disease process, evaluate the effect of treatment [7,8]. EMG signals are also widely used for prosthetic device control. It provides imitation of muscle movements with biological marks transferred in prosthesis applications such as hand, elbow and wrist. In these applications, the performance of the proposed algorithms for human–machine interaction gains great importance [9,10]. Significant advances have been made in the identification of forearm movements by using sEMG signals for human machine interaction. These applications are also widely used in the recognition of finger movements [11–13]. Today, the control of finger movements with sEMG signals is widely studied. Pattern recognition methods are used to provide more functionality in performing this control and the performance of various methods are evaluated. However, prosthetic devices for upper limb amputations still do not have sufficient success. A perception strategy developed in myoelectric systems is needed to increase the level of success [14,15]. In this study, a novel method is proposed for finger movements recognition. The proposed method is based on machine learning and can be used in prosthetic device control.

Today, amputation of the hand and finger limbs seen in many people in the world is encountered and various devices and methods have been proposed to ensure that these individuals are brought to real life quality. In this study, a novel method is proposed on the classification of fingerprint movements. The proposed multi-centered binary pattern (MCBP) is a hand-model learning approach. This model contains

* Corresponding author.

https://doi.org/10.1016/j.bspc.2021.103153
Received 27 October 2020; Received in revised form 1 September 2021; Accepted 7 September 2021
Available online 16 September 2021

multilevel feature extraction, feature selection and fine-tuned classification. In the hand-crafted feature creation, textural and statistical generators have been used. In order to use effectiveness of these feature generators, MCBP, which is a textural feature selector and the commonly used 15 statistical moments have been used to generate 30 statistical features. However, the hand-crafted feature extractors cannot generate features at high level. Discrete Wavelet Transform (DWT) has been used to create levels (sub-bands). By extracting features from these sub-bands, high level features are obtained. RFNCA is utilized as feature selector to use benefits of ReliefF and NCA together. In the classification phase, fine-tuned SVM and k-NN, which are shallow classifiers are used to classify finger movements. Our proposed approach has been tested on a public sEMG dataset [16]. The main purpose of this study is to effectively recognize the finger movements and thus, ensure that patients experiencing upper limb amputation maximize their daily life performance.

Today, amputation of the hand and finger limbs seen in many people worldwide. Moreover, some cerebral palsy patients cannot use their hands or fingers effectively. To remedy daily of these people, artificial intelligence and sEMG signals have been used to create a new generation intelligent orthotics and prosthesis. Therefore, hand and finger movements classification are crucial work area for advanced biomedical signal processing, computer sciences and feature engineering. A novel hand-crafted finger movement classification method is proposed in this article. The main phases of the proposed finger movements classification method are given as follows. sEMG signals are utilized as input to classify 15 finger movements. By using these sEMG signals, three cases are defined. These cases are created to denote universal/general success of the proposed model. The first case uses raw sEMG signals and there are 360 observations. The sEMG signals is divided into frame length of 5000 and 5760 observations to be evaluated in the second case. In third case, the sEMG signals are divided into frames length of 4000 and 7200 observations. These cases are created to show success of the MCBP-RFNCA classification model on small and big sEMG signals corpora. By using one dimensional discrete wavelet transform (1D-DWT) [17], four sub-bands are created and 1D-DWT is utilized as spooling method in this work. The proposed MCBP extracts 256 features from each level of the channels. Also, 30 features are generated employing the proposed statistical extractor. The generated features from each level of the channels are concatenated. A hybrid feature selector which is called as RFNCA (ReliefF [18] and Neighborhood Component Analysis [19] based feature selector) selects 286 (the best results are achieved by selecting 286 features) most distinctive features. Two fine-tuned conventional classifiers which are k-Nearest Neighbor (k-NN) [20] and support vector machine (SVM) [21] are used.

We proposed a new feature extraction function, which is called as MCBP. In the MCBP, center pixel can be changed parametrically. Moreover, a new multilevel feature extraction method based on MCBP, and DWT is presented. The generated features are selected by hybrid and iterative feature selector. Novelties of this research and the key contributions of the proposed MCBP based finger classification approach can be summarized as follows.

- Binary Pattern (BP) [22] is an effective and successful feature extraction method for images and signals. Therefore, BP has been widely used in image and signal processing. To comprehensively generate features by using BP, a novel BP like feature extractor (MCBP) is presented and it achieved higher performance for finger movement classification.
- We defined three cases by using sEMG signals to classify finger movements. By using these cases, success of the frame-based classification method is presented.
- Our proposed MCBP-RFNCA model is a high accurate model. Moreover, this model has low time complexity.

The rest of the paper is organized as follows: in Section 2, related works are given. In Section 3, details of the experimental data are presented. In Section 4, feature extraction, feature selection, and classification model architectures are explained. Experimental results are presented in Section 5. Discussions are given in Section 6 and conclusions are given in Section 7.

2. Related works

Different studies are presented in the literature to process sEMG signals. Rabin et al. [23] proposed a human hand movements method, which was based on short time Fourier transform. UCI dataset [24] was used in the experiments. For single subject classification, accuracy was calculated as 94.80%. The limitations of their study are that there are 5 subjects in the dataset used. It also includes six movements. Mukhopadhyay and Samui [25] presented a method based on deep learning. The proposed scheme achieved 98.88% accuracy. Their method has high complexity. Tuncer et al. [26] utilized ternary pattern and discrete wavelet transform in their proposed model. They achieved 99.14% accuracy with the proposed framework. The limitation of the proposed method is the usage of small dataset. Naik and Nguyen [27] used artificial neural network for human hand movements classification and achieved 92% accuracy. The limitation of this method is that it has high complexity. Rasheed et al. [28] proposed a hybrid classifier fusion method for motor unit potential classification using EMG signal. Their study can be evaluated with another known dataset [29,30]. The proposed model achieved 93.90% accuracy. Xi et al. [31] employed wavelet coherence and magnitude square coherence in their proposed scheme. The limitation of the proposed method is that it has low accuracy (83.50%). Simão et al. [32] used recurrent neural networks for gestures classification. They used two different datasets, which are UC2018 DualMyo data set [33] and NinaPro DB5 data set [34]. The proposed method achieved 95% accuracy. Their method has high complexity. The limitation of the Zhang et al. method [35] is its high complexity. Zhang et al. [35] employed Deep belief network. They achieved 100.0% accuracy with UCI machine learning repository [24]. Khushaba et al. [36] proposed a method for prosthetic fingers control using sEMG signals. They used Hjorth Time Domain Parameters, AutoRegressive Model and achieved 90% accuracy. Their study can be evaluated with bigger dataset. Bhattachargee et al. [37] used ensemble learning and fast Fourier transformation for finger movement classification employing Khushaba dataset [38]. They achieved 98.50% accuracy. The limitation of their study is that a larger dataset can be preferred. Purushothaman and Vikas [39] utilized Particle swarm optimization, Ant colony optimization and but achieved low accuracy rate (88.89%) with Khushaba and Kodagoda dataset [16]. Jafarzadeh et al. [40] presented a method based on convolutional neural networks using Khushaba and Kodagoda dataset [16]. The proposed method by Jafarzadeh et al. [40] has high complexity and achieved 91.26%. Phinyomark and Scheme [41] employed Higher order crossings with Khushaba and Kodagoda dataset [16] and achieved low accuracy (85.80%).

Hand-crafted features-based models have lower computational complexity, but they have limited performances with big datasets. Deep learning-based models attained high performance but the time complexities of them are very high. In order to overcome this tradeoff, we proposed a hand-modeled learning approach using a new architecture. Our main motivation is to yield high performance with low time-complexity. Moreover, we defined three cases to denote classification success of the proposed model on both large and small sEMG datasets.

3. Dataset

The data is collected by Kushaba and Kodagoda [16]. The used sEMG signals were collected from eight subjects. 6 of them male and 2 of them female. The subjects were healthy they have no neurological disorders. These subjects sit an armchair and Delsys sEMG sensors were used to collect these signals with 8 channels. The age range of the subjects is

20–35. These signals are collected at 4000 Hz. The analog signals were converted to 12-bit. 15 finger movements were collected; hence, this dataset has 15 classes. The collected movements are shown in Fig. 1.

Each class has 24 observations and there are 360 observations in this dataset. The length of each observation is 20 s. In this respect, this dataset is a small sEMG dataset. In order to create large sEMG signals corpora using this dataset, this dataset has been divided into segments and Case 2-3 are defined to evaluate MCBP-RFNCA classification model on a large sEMG signal dataset. The details of these cases are given in Section 4.

4. Proposed Multi-Centered binary pattern based finger movement classification method

The proposed framework uses MCBP, statistical feature generator, 1D-DWT, RFNCA selector and fine-tuned classifiers together. The novelty of the proposed model is MCBP. In the one-dimensional local binary pattern, overlapping blocks with a length of nine and the fifth value of each block is utilized as center value. To extract comprehensive features from images, a multiple center binary pattern (MCBP) is proposed. In the MCBP, center value of the overlapping block is parametric, and users can change center value. Furthermore, statistical features have been extracted. 1D-DWT have been used to create sub-bands and these sub-bands have been used to generate features at high level. The proposed MCBP and statistical feature generators extract features from wavelet sub-bands and sEMG signals. The used dataset contains sEMG signals with eight channels. Therefore, our fused feature generator extracts feature vector from each channel. The graphical illustration of the proposed MCBP-RFNCA classification model is shown in Fig. 2.

Fig. 2 illustrates that the proposed MCBP uses variable center values in each level of each channel of the employed sEMG signal. The proposed MCBP extracts $256 \times 5 = 1280$ textural features from each

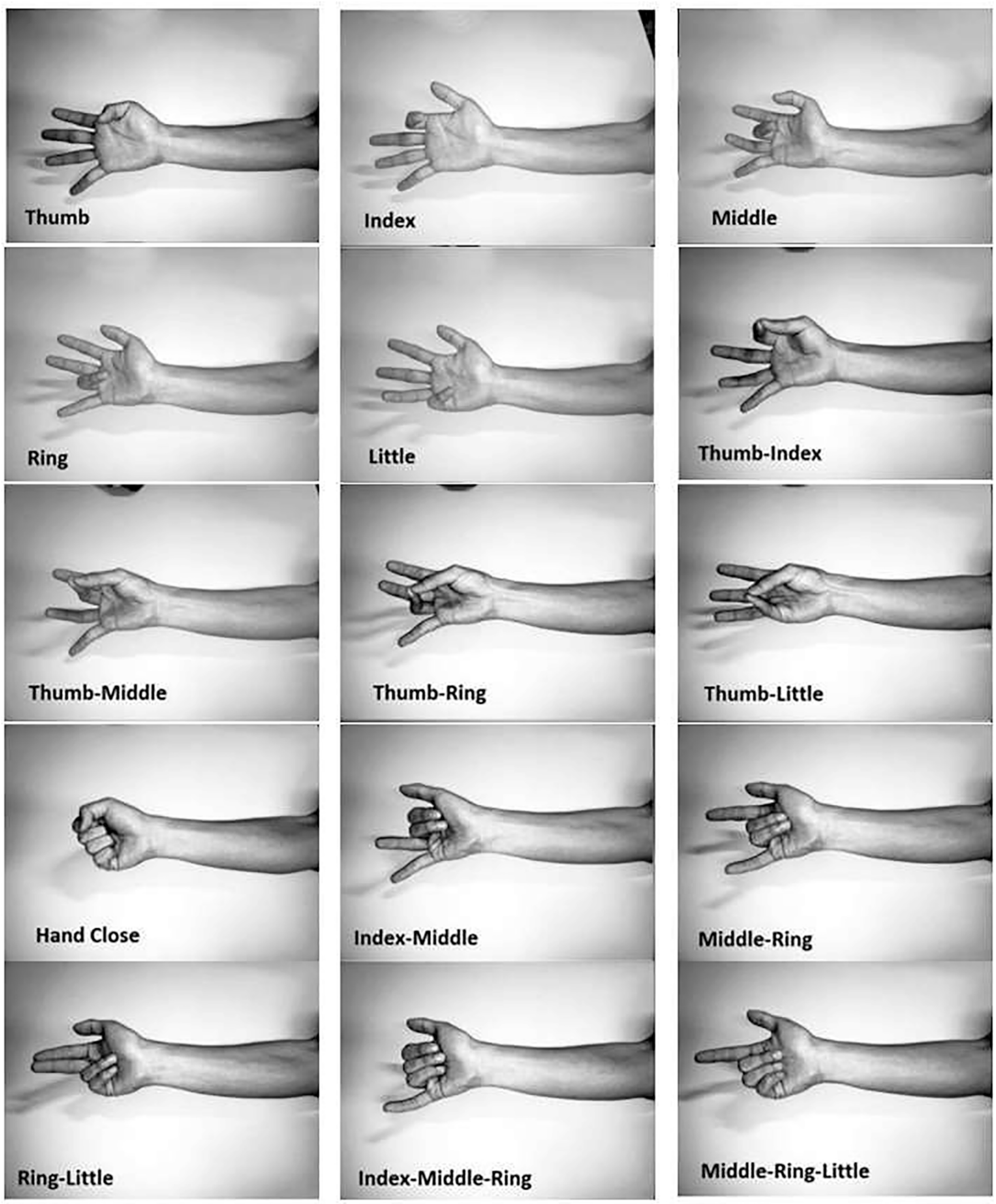

Fig. 1. The used finger movements.

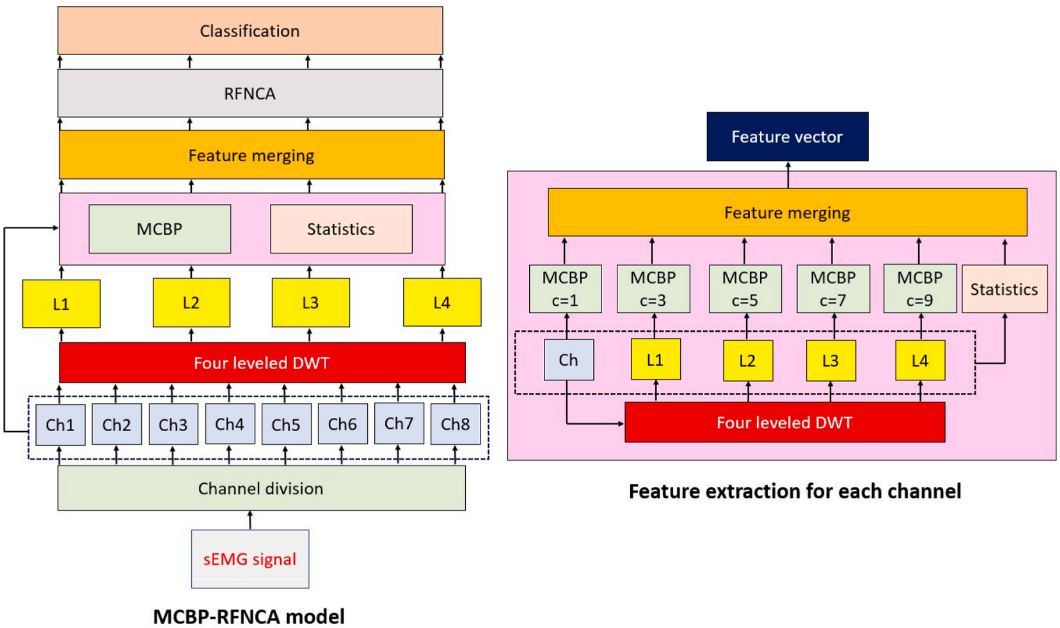

Fig. 2. Graphical illustration of the proposed MCBP-RFNCA signal classification model. Herein, Ch defines channel, L1, L2, L3, L4 are low-pass filter sub-band, and c is index of the center pixels.

channel of the used sEMG. Moreover, 15 statistical moments have been used to extract 30 statistical features and $30 \times 5 = 150$ statistical features are generated in each channel. Hence, 1430 features are generated from each channel. The used sEMG signals has eight channels. Therefore, the length of the generated feature vector is equal to $1430 \times 8 = 11440$. In order to both decrease length of the generated feature vector and increase classification performance, RFNCA has been applied to this feature vector. RFNCA is a two layered feature selection method, which utilizes ReliefF and NCA together. In RFNCA, firstly, ReliefF is applied to the feature vector to eliminate the redundant features. In the second step of the RFNCA, NCA is applied to the selected features by ReliefF and the most discriminative 286 (256 + 30) features are chosen. The chosen 286 features are forwarded to fine-tuned k-NN and SVM. Bayesian optimization technique has been used to tune k-NN and SVM. 10-fold cross-validation technique has also been used to validate results.

4.1. Feature extraction

In this section, we presented the proposed MCBP based finger movement classification method. The employed sEMG signals have 8 channels and we extract features from each channel by using a multilevel method. In here, 1D-DWT is utilized as a polling method to reduce dimensionality of the signal and remove noises.

Step 0: Load sEMG signals with 8 channels.

Step 1: Divide each channel.

Step 2: Apply four levels 1D-DWT with sym4 filter and calculate low pass filter sub-bands. The symlet 4 mother wavelet function is a widely used function in the DWT. Moreover, this filter has used to remove noises.

$$[L_1^i, H_1^i] = DWT(Ch_i, sym4), i = \{1, 2, \cdots, 8\} \tag{1}$$

$$[L_2^i, H_2^i] = DWT(L_1^i, sym4) \tag{2}$$

$$[L_3^i, H_3^i] = DWT(L_2^i, sym4) \tag{3}$$

$$[L_4^i, H_4^i] = DWT(L_3^i, sym4) \tag{4}$$

where Ch_i is ith channels of the sEMG signal, L_k^i and H_k^i represent kth level low and high pass filter coefficients of the Ch_i respectively. The calculated sub-bands of each channel are used for feature generation. Eqs. (1) – (4) define the four leveled DWT. Herein, low pass filter sub-bands (approximate bands) have been used to generate features. Multilevel DWT is an effective decomposition model for biomedical signal processing. It can decompose signals into sub-band with different frequencies. Moreover, time complexity of the feature generation with multilevel DWT is $O(nlogn)$. By using wavelet packet decomposition (WPD), all sub-bands are used to generate features and time complexity of WPD is $O(2^n)$. Moreover, WPD increases dimension of the extracted features, and it makes feature selection difficult. Thus, we used multilevel DWT in this step.

Step 3: Generate textural features using MCBP feature extractor. The details of the MCBP based textural feature extraction is given below.

MCBP is one of variants of the BP. This method is inspired by dynamic center based BP [42]. In the dynamic center-based BP, all values of the 9 sized overlapping blocks are utilized as center respectively but selected values are utilized as center in the proposed MCBP. In this study, odd-indexed values (1st, 3rd, 5th, 7th and 9th values) are selected as center. As seen from Fig. 3, the center values are changed according to levels. Steps of the proposed MCBP are:

Step 3.1: Divide channel of low pass filter coefficient into 9 sized overlapping blocks.

Step 3.2: Generate MCBP signals by using parametric center based BP signal creation procedure. This procedure is given in Algorithm 1.

Algorithm 1. Procedure of parametric BP signal generation.

Procedure: $PBP(Signal, index)$

Input: Signal (Channel of sEMG signal or low pass filter of a channel) with size of *length***Output:** BP signal (BPS) with size of$length-8$
1: **for** d = 1 to $length-8$ **do**2: $blck = Signal(d:d+8)$; // 9 sized overlapping block creation.3: $counter = 1$; // Define counter to generate features.4: $BPS(d) = 0$; // Assign first value of the BPS as 0.5: **for** t = 1 to 9 **do**6: **if**t! = $index$ **then**7:$BPS(d) = BPS(d) + [blck(t) > blck(index)] \times 2^{8-counter}$;8: $counter = counter + 1$;9: **end if**10: **end for** t11: **end for d**

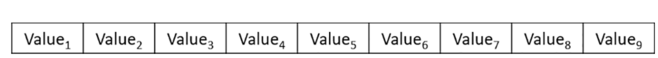

Fig. 3. Illustration of the 9 sized overlapping block of a channel or low pass filter of a channel. Observations of the used blocks are named as value.

Step 3.3: Extract histogram of the *BPS* with length of 256.

Step 3.4: Concatenate histograms.

The proposed MCBP based feature extraction procedure is mathematically defined as below.

$$histo_1 = HistExt(PBP(Ch_i, 1)) \quad (5)$$

$$histo_2 = HistExt\left(PBP\left(L_1^i, 3\right)\right) \quad (6)$$

$$histo_3 = HistExt\left(PBP\left(L_2^i, 5\right)\right) \quad (7)$$

$$histo_4 = HistExt\left(PBP\left(L_3^i, 7\right)\right) \quad (8)$$

$$histo_5 = HistExt\left(PBP\left(L_4^i, 9\right)\right) \quad (9)$$

$$tf^i = histo_1|histo_2|histo_3|histo_4|histo_5 \quad (10)$$

where $histo_i$ ith histogram of the generated MCBP signal, $HistExt(.)$ is histogram extraction function, tf^i defines the generated textural features with length of 1280 from ith channel and | is combining operator.

Step 4: Generate statistical features using statistical moments. Herein, we used 15 statistical moments and these moments have been applied to the used signal and absolute value of the signal. These moments are skewness, kurtosis, maximum, minimum, median, average, standard deviation, variance, root mean square, Higuchi, Shannon entropy, sure entropy, log entropy, energy and range of the sub-bands. The statistical feature generation/extraction is explained in below.

$$s_1 = StExt(Ch_i) \quad (11)$$

$$s_2 = StExt(L_1^i) \quad (12)$$

$$s_3 = StExt(L_2^i) \quad (13)$$

$$s_4 = StExt(L_3^i) \quad (14)$$

$$s_5 = StExt(L_4^i) \quad (15)$$

$$sf^i = s_1|s_2|s_3|s_4|s_5 \quad (16)$$

In Eqs. (11) – (16), the statistical feature generation from each channel is defined. Herein, $StExt(.)$ defines statistical feature extraction function, s_j is jth statistical feature vector with a length of 30 and sf^i represents merged statistical features extracted from ith channel.

Step 5: Concatenate features to obtain final feature vector

$$tf = tf^1\left|tf^2\right|\cdots|tf^8 \quad (17)$$

$$sf = sf^1\left|sf^2\right|\cdots|sf^8 \quad (18)$$

where tf represents final textural feature vector with size of 1280x8 = 10240 and sf defines final merged statistical feature vector with a length of 150x8 = 1200. By merging tf and sf, the final feature (ff) vector with a length of 11,440 is obtained.

$$ff = sf|tf \quad (19)$$

Step 6: Normalize ff in range of to 0 from 1 using min–max normalization.

$$ff = \frac{ff^k - ff^k_{min}}{ff^k_{max} - ff^k_{min}}, k \in \{1, 2, \cdots, 11440\} \quad (20)$$

4.2. Feature selection

In the feature generation and concatenation phase, 11,440 features are obtained from a sEMG signal. ReliefF and NCA are used together to select most distinctive ones from the final feature vector. The used feature selector is 2-layered. Both ReliefF and NCA are weight-based feature selectors. Small weights describe less discriminative (redundant) features. ReliefF also generates both negative and positive weights, but NCA generates only positive weights. Especially, negative weights describe redundant features according to ReliefF. Therefore, RFNCA eliminates redundant features in the first step according to weights of the ReliefF. Then, 286 most discriminative features are selected by using weights of NCA. We also tested ReliefF, minimum redundancy maximum relevance (mRMR), NCA and Chi2 feature selectors and we create combinations. The best resulted selector is RFNCA. The steps of this section (RFNCA) are also given in below.

Step 6: Calculate weights of the ReliefF.

$$weights^{RF} = RF(ff, target) \quad (21)$$

Herein, $weights^{RF}$ are the generated weights using ReliefF ($RF(.,.)$) selector and *target* defines actual labels.

Step 7: Select positive weighted features

$$feat^{RF}(c) = \begin{cases} ff(i) and c = c+1, weights^{RF}(i) > 0 \\ continue, weights^{RF}(i) \leq 0 \end{cases}, i \in \{1, 2, \cdots, 11400\} \quad (22)$$

Herein, selected features by ReliefF is $feat^{RF}$.

Step 8: Calculate weights ($weights^{NCA}$) of the $feat^{RF}$ by using NCA.

$$weights^{NCA} = NCA(feat^{RF}, target) \quad (23)$$

Step 9: Select 286 most weighted features.

$$[sorted, value] = sort(weights^{NCA}, descending) \quad (24)$$

$$ft(j) = feat^{RF}(value(j)), j \in \{1, 2, \cdots, 286\} \quad (25)$$

where ff is selected final 128 features, *value* is index of the sorted $weights^{NCA}$.

4.3. Classification

The selected 286 features are used as input of the used classifiers. K-NN [20] and SVM [21] are used in this phase. These classifiers are well known and mostly used conventional classifier. 10-fold cross-validation was chosen to obtain test results of the used classifiers. Moreover, the hyperparameters of these classifiers (k-NN) were tuned using Bayesian optimization technique. The attributes of the Bayesian optimizer are given as follows. Acquisition function is improvement per second, iterations is 30 and training time limit is false. The hyperparameters of the fine-tuned SVM and k-NN are demonstrated in Fig. 4.

Step 10: Calculate validation predictions by using the used fine-tuned classifiers by using Bayesian optimizer.

5. Results

The proposed MCBP-RFNCA model was implemented by a simple configured personal computer with 32 GB main memory, intel i7-9700 processor with 3 GHz clock and 512 GB solid state disk. Moreover, Windows 10.1 ultimate was used as operating system. The proposed framework was coded on the MATLAB (2020b) programming environment. m files were used to program the used feature generator and RFNCA selector. In the classification phase, MATLAB Classification Learner (MCL) tool was used. To comprehensively evaluate the presented MCBP-RFNCA based finger movement classification method, three cases were defined, and details of these cases are given below.

Case 1:. *The used finger movement dataset contains* 360 *sEMG signals with* 15 *clusters. In this case,* 80,000 *samples* (20 *s*) *of sEMG signals are utilized as input of the proposed MCBP-RFNCA based method. There are* 24 *sEMG signals in each cluster.*

Case 2:. 80,000 *samples of sEMG signals are divided in* 5000 (1.25 *s*) *sized frames. Therefore,* 5760 *sEMG signal instance are obtained and each cluster contains* 384 *observations.*

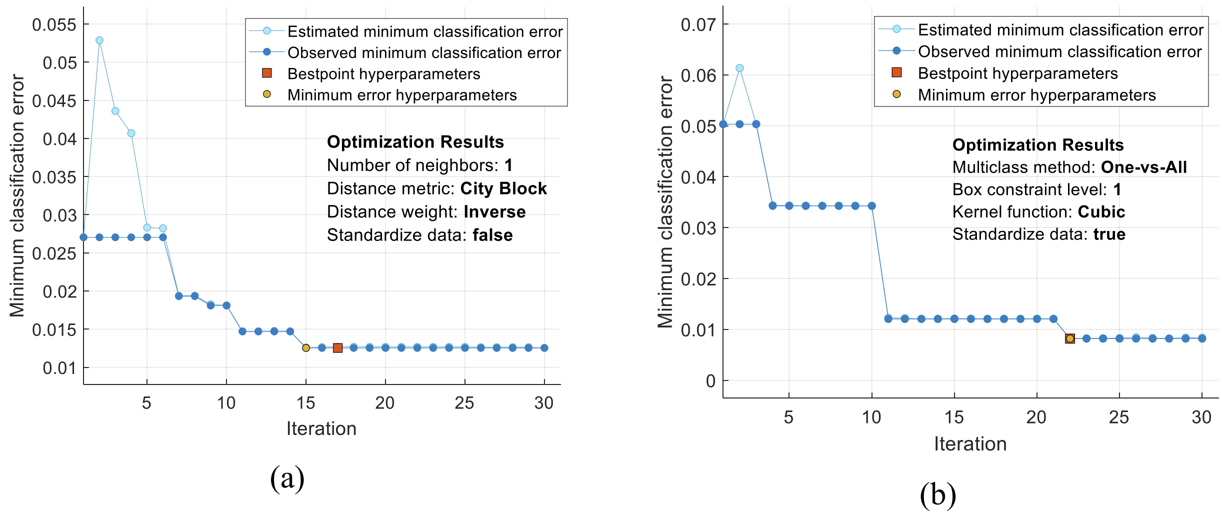

Fig. 4. Fine-tuned hyperparameters of the used (a) kNN and (b) SVM classifiers.

Case 3:. *Each sEMG signal are divided into non-overlapping frames with a length of* 1 *s* (4000). *In* Case 3, 7200 *observations are obtained and there are* 480 *observations in each cluster.*

The original dataset has evaluated using Case 1. By using Case 2 and 3, more observations (5760 and 7200 observations) have obtained. The main purpose of creating these cases (Case 2 and Case 3) is to denote high classification ability of the proposed MCBP-RFNCA model on huge/large sEMG signal datasets.

Overall precision, accuracy, geometric mean, F1-score and Cohen's Kappa performance evaluation metrics have been used to test the proposed MCBP-RFNCA approach on the finger movement dataset. These performance metrics were calculated deploying fine-tuned k-NN and SVM with 10-folds cross validation. The obtained results according to cases are tabulated in Table 1.

Results (see Table 1) clearly indicated that the best resulted classifier is SVM for all cases and it achieved 99.17%, 99.70% and 99.62% classification accuracies for Case 1, Case 2 and Case 3 respectively. Moreover, the proposed MCBP-RFNCA model reached over 98% performance evaluation results for all cases using k-NN or SVM.

Time complexity of the proposed MCBP based finger movement classification was also calculated. To clearly calculate time complexity of this method, steps and time complexity of each step were listed in Table 2.

Table 2
Calculation of time complexity of the proposed MCBP based finger movement classification method.

Steps	Time complexity
0: Load sEMG signals	
1: for k = 1 to N do // N is number of signals	
2: $cc = 1$; // Define counter to concatenate features	$O(N)$
3: for i = 1 to 8 do	
4:$Ch = s(:, i)$;	$O(8N)$
5: for j = 1 to 5 do	
6: *X(k,(cc-1)*256 + 1:cc*256) = [bp(s,(j-1)*2 + 1) StExt(s)];*	$O(\frac{40NT}{2^{j-1}})$
7: $[l, h] = dwt(Ch,'sym4')$; // Apply DWT	$O(\frac{40NT}{2^{j-1}})$
8:$Ch = l$	$O(40N)$
9: $cc = cc + 1$;	$O(40N)$
10: end for j	
11: end for i	
12: end for k	
13: Normalize X	$O(mn)$
14: Select features by using RFNCA	$O(mnk)$
15: Classify selected features	$O(286k)$
Total:$O(89N + 120NTlogT + mn + mnk + 286k)$	

where N is number of sEMG signals, m and n are width and height of the extracted features (X), T is length of the sEMG signal, k is classification coefficients. Time complexity of the proposed MCBP based classification method was calculated as$O(NTlogT + mnk)$

6. Discussions

In this work, one dimensional binary pattern like feature extractor (MCBP) is presented. MCBP and statistic based multileveled feature extraction method extracts 11,440 features from each sEMG signal. By using RFNCA, 286 features are selected. Three cases are defined, and these cases use raw sEMG signals and segmented (framed) sEMG signals respectively. Two fine-tuned conventional classifiers are chosen and results clearly demonstrated that high classification results were obtained for Case 2 using proposed approach. The best results have calculated SVM classifier for all cases and SVM reached over 99% classification accuracy. In order to select the best classifiers, the decision tree (DT), linear discriminant (LD), naïve bayes (NB), SVM, k-NN, bagged tree (BT) and subspace discriminant (SD) classifiers were tested, and the obtained classification accuracies were shown in Fig. 5.

Fig. 5 indicated that the best classifiers are k-NN and SVM. Therefore, we tuned hyperparameters of these classifiers to attain the maximum classification accuracy.

Khushaba and Kodagoda [16] collected the used finger movement dataset. They reached higher than 95.61% classification accuracy. We used three cases to indicate classification ability of our proposed approach clearly. These cases contain 360, 5760 and 7200 observations respectively. In this respect, performance of our MCBP-RFNCA based model has denoted using both small and large sEMG datasets. The proposed MCBP-RFNCA based finger movement classification model attained 99.17%, 99.70% and 99.62% accuracies on Case 1, Case 2 and Case 3 respectively.

Table 1
Calculated results (%) of the Case 1 by using k-NN and SVM.

Case	Classifier	Accuracy	Precision	Geometric mean	F1-Score	Cohen's Kappa
Case 1	k-NN	98.89	98.93	98.87	98.89	98.81
	SVM	99.17	99.20	99.15	99.17	99.11
Case 2	k-NN	99.48	99.48	99.48	99.48	99.44
	SVM	99.70	99.71	99.70	99.70	99.68
Case 3	k-NN	99.57	99.57	99.57	99.57	99.54
	SVM	99.62	99.63	99.62	99.62	99.60

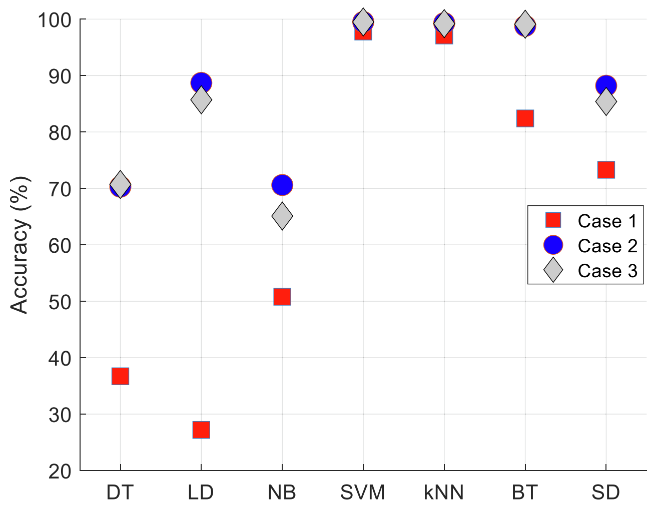

Fig. 5. The classification accuracies of the seven classifiers for three cases.

We presented a multileveled method and time complexity of this method was also calculated. According to calculation (See Table 4), time complexity of the proposed MCBP based method was calculated as $O(NTlogT + mnk)$.

The advantages of the proposed MCBP based finger movement classification method are as follows.

- The proposed MCBP based classification method achieved over 99% classification accuracies for three different cases.
- The proposed MCBP-RFNCA based model reached high performance on both small and large sEMG datasets (using three cases).
- The proposed MCBP-RFNCA based method has low time complexity and high classification accuracy. Therefore, there is no need to use deep learning model to classify these sEMG signals.
- A robust classification approach is presented because results were calculated by using 10-fold cross validation.

Limitation of this research is given as follows. Since we used publicly available sEMG dataset, this dataset has limited number of subjects. Huge sEMG dataset can be collected from different medical centers and the number of subjects can be increased. In near future, we are planning to collect a huge dataset from variable centers and different sEMG devices.

7. Conclusions

In this work, a novel MCBP based sEMG signal classification method is presented to classify finger movements. Hence, a new and multilevel feature extraction method is presented to extract valuable features by using MCBP. MCBP is a novel version of the BP, and it uses odd-indexed values as center. 1D- DWT was utilized as a decomposition method and created sub-bands to generate features at high levels. MCBP and statistical moments are utilized to extract features from every sub-band of the channels. 11,440 features are extracted from eight channel sEMG signal. In the feature selection phase, ReliefF and NCA are used together to create RFNCA in this study. The main reason for using ReliefF and NCA together is to choose the effective features. RFNCA selects 286 most valuable features from 11,440 sized feature set. Two fine-tuned conventional classifiers were selected in the classification phase. Three cases namely Case 1, Case 2 and Case 3 were also utilized in the experiments, and these cases contain 360, 5760 and 7200 observations respectively. Our proposed approach achieved 99.17%, 99.70% and 99.62% accuracies for the Case 1, Case 2 and Case 3, respectively deploying fine-tuned SVM. By using the proposed MCBP-RFNCA based method, approximately 4% better accuracy was achieved than other method.

In future works, an intelligent system can be developed for finger movements classification with proposed method utilizing big number of subjects. A prosthetic hand or glove can be designed for amputee subjects and patients.

Ethical approval

The used dataset is publicly and freely available dataset which can be downloaded from https://www.rami-khushaba.com/electromyogram-emg-repository.html. The ethical approval of the used dataset was provided by School of Computing and Mathematics, Plymouth University.

CRediT authorship contribution statement

All algorithm codes are written and run by Turker Tuncer. Part of Introduction and results are written by Turker Tuncer. Part of Introduction and Conclusion are written by Sengul Dogan. Part of Introduction, Methods, Results and Discussion are written by Abdulhamit Subasi. The whole manuscript revised by Abdulhamit Subasi.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] A.L. Coelho, C.A. Lima, Assessing fractal dimension methods as feature extractors for EMG signal classification, Eng. Appl. Artif. Intell. 36 (2014) 81–98.
[2] K. Najarian, R. Splinter, Biomedical signal and image processing, CRC press2005.
[3] Y. Uwadaira, A. Shimotori, A. Ikehata, K. Fujie, Y. Nakata, H. Suzuki, H. Shimano, K. Hashimoto, Logistic regression analysis for identifying the factors affecting development of non-invasive blood glucose calibration model by near-infrared spectroscopy, Chemometrics Intell. Lab. Syst. 148 (2015) 128–133.
[4] M. Borghetti, E. Sardini, M. Serpelloni, Sensorized glove for measuring hand finger flexion for rehabilitation purposes, IEEE Trans. Instrum. Meas. 62 (2013) 3308–3314.
[5] F.J. Theis, A. Meyer-Bäse, Biomedical signal analysis: Contemporary methods and applications, MIT Press, 2010.
[6] A. Subasi, S.M. Qaisar, Surface EMG signal classification using TQWT, Bagging and Boosting for hand movement recognition, J. Ambient Intell. Hum. Comput. (2020), https://doi.org/10.1007/s12652-020-01980-6.
[7] M.-F. Lucas, A. Gaufriau, S. Pascual, C. Doncarli, D. Farina, Multi-channel surface EMG classification using support vector machines and signal-based wavelet optimization, Biomed. Signal Process. Control 3 (2008) 169–174.
[8] A.H. Al-Timemy, R.N. Khushaba, G. Bugmann, J. Escudero, Improving the performance against force variation of EMG controlled multifunctional upper-limb prostheses for transradial amputees, IEEE Trans. Neural Syst. Rehabil. Eng. 24 (2015) 650–661.
[9] L. Liu, P. Liu, E.A. Clancy, E. Scheme, K.B. Englehart, Electromyogram whitening for improved classification accuracy in upper limb prosthesis control, IEEE Trans. Neural Syst. Rehabil. Eng. 21 (2013) 767–774.
[10] A. Waris, I.K. Niazi, M. Jamil, K. Englehart, W. Jensen, E.N. Kamavuako, Multiday evaluation of techniques for EMG-based classification of hand motions, IEEE J. Biomed. Health. Inf. 23 (2018) 1526–1534.
[11] F. Tenore, A. Ramos, A. Fahmy, S. Acharya, R. Etienne-Cummings, N.V. Thakor, Towards the control of individual fingers of a prosthetic hand using surface EMG signals, 2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE, 2007, pp. 6145-6148.
[12] N. Hu, P.H. Chappell, N.R. Harris, Finger Displacement Sensing: FEM Simulation and Model Prediction of a Three-Layer Electrode Design, IEEE Trans. Instrum. Meas. 68 (2018) 1432–1440.
[13] P. Bellitti, A. De Angelis, M. Dionigi, E. Sardini, M. Serpelloni, A. Moschitta, P. Carbone, A Wearable and Wirelessly Powered System for Multiple Finger Tracking, IEEE Trans. Instrum. Meas. 69 (2020) 2542–2551.
[14] X. Li, O.W. Samuel, X. Zhang, H. Wang, P. Fang, G. Li, A motion-classification strategy based on sEMG-EEG signal combination for upper-limb amputees, J. NeuroEng. Rehabil. 14 (2017) 2.
[15] A.J. Young, L.H. Smith, E.J. Rouse, L.J. Hargrove, Classification of simultaneous movements using surface EMG pattern recognition, IEEE Trans. Biomed. Eng. 60 (2012) 1250–1258.
[16] R.N. Khushaba, S. Kodagoda, Electromyogram (EMG) feature reduction using mutual components analysis for multifunction prosthetic fingers control, 2012

12th International Conference on Control Automation Robotics & Vision (ICARCV), IEEE, 2012, pp. 1534-1539.
[17] H. Tian, W. Ji, A digital video watermarking scheme based on 1D-DWT, 2010 International Conference on Biomedical Engineering and Computer Science, IEEE, 2010, pp. 1-3.
[18] M. Robnik-Šikonja, I. Kononenko, Theoretical and empirical analysis of ReliefF and RReliefF, Mach. Learn. 53 (2003) 23–69.
[19] S. Raghu, N. Sriraam, Classification of focal and non-focal EEG signals using neighborhood component analysis and machine learning algorithms, Expert Syst. Appl. 113 (2018) 18–32.
[20] D.A. Adeniyi, Z. Wei, Y. Yongquan, Automated web usage data mining and recommendation system using K-Nearest Neighbor (KNN) classification method, Appl. Comput. Inform. 12 (2016) 90–108.
[21] M.E. Mavroforakis, S. Theodoridis, A geometric approach to support vector machine (SVM) classification, IEEE Trans. Neural Net. 17 (2006) 671–682.
[22] T. Ojala, M. Pietikäinen, T. Mäenpää, Gray scale and rotation invariant texture classification with local binary patterns, Euro. Conf. Comput. Vision, Springer (2000) 404–420.
[23] N. Rabin, M. Kahlon, A. Ratnovsky, Classification of human hand movements based on EMG signals using nonlinear dimensionality reduction and data fusion techniques, Expert Syst. Appl. 113281 (2020).
[24] C. Sapsanis, G. Georgoulas, A. Tzes, EMG based classification of basic hand movements based on time-frequency features, 21st Mediterranean Conference on Control and Automation, IEEE, 2013, pp. 716-722.
[25] A.K. Mukhopadhyay, S. Samui, An experimental study on upper limb position invariant EMG signal classification based on deep neural network, Biomed. Signal Process. Control 55 (2020), 101669.
[26] T. Tuncer, S. Dogan, A. Subasi, Surface EMG signal classification using ternary pattern and discrete wavelet transform based feature extraction for hand movement recognition, Biomed. Signal Process. Control 58 (2020), 101872.
[27] G.R. Naik, H.T. Nguyen, Nonnegative matrix factorization for the identification of EMG finger movements: Evaluation using matrix analysis, IEEE J. Biomed. Health. Inf. 19 (2014) 478–485.
[28] S. Rasheed, D.W. Stashuk, M.S. Kamel, A hybrid classifier fusion approach for motor unit potential classification during EMG signal decomposition, IEEE Trans. Biomed. Eng. 54 (2007) 1715–1721.
[29] S. Rasheed, D. Stashuk, M. Kamel, Adaptive certainty-based classification for decomposition of EMG signals, Med. Biol. Eng. Compu. 44 (2006) 298–310.
[30] S. Rasheed, D. Stashuk, M. Kamel, Adaptive fuzzy k-NN classifier for EMG signal decomposition, Med. Eng. Phys. 28 (2006) 694–709.
[31] X. Xi, C. Ma, C. Yuan, S.M. Miran, X. Hua, Y.-B. Zhao, Z. Luo, Enhanced EEG–EMG coherence analysis based on hand movements, Biomed. Signal Process. Control 56 (2020), 101727.
[32] M. Simão, P. Neto, O. Gibaru, EMG-based online classification of gestures with recurrent neural networks, Pattern Recogn. Lett. 128 (2019) 45–51.
[33] M. Simao, P. Neto, O. Gibaru, Improving novelty detection with generative adversarial networks on hand gesture data, Neurocomputing 358 (2019) 437–445.
[34] S. Pizzolato, L. Tagliapietra, M. Cognolato, M. Reggiani, H. Müller, M. Atzori, Comparison of six electromyography acquisition setups on hand movement classification tasks, PLoS ONE 12 (2017).
[35] J. Zhang, C. Ling, S. Li, EMG Signals based Human Action Recognition via Deep Belief Networks, IFAC-PapersOnLine 52 (2019) 271–276.
[36] R.N. Khushaba, S. Kodagoda, M. Takruri, G. Dissanayake, Toward improved control of prosthetic fingers using surface electromyogram (EMG) signals, Expert Syst. Appl. 39 (2012) 10731–10738.
[37] C.K. Bhattachargee, N. Sikder, M.T. Hasan, A.-A. Nahid, Finger movement classification based on statistical and frequency features extracted from surface EMG signals, 2019 International Conference on Computer, Communication, Chemical, Materials and Electronic Engineering (IC4ME2), IEEE, 2019, pp. 1-4.
[38] R. Khushaba, Electromyogram (EMG) Repository, https://www.rami-khushaba.com/electromyogram-emg-repository.html, 2019.
[39] G. Purushothaman, R. Vikas, Identification of a feature selection based pattern recognition scheme for finger movement recognition from multichannel EMG signals, Australas. Phys. Eng. Sci. Med. 41 (2018) 549–559.
[40] M. Jafarzadeh, D.C. Hussey, Y. Tadesse, Deep learning approach to control of prosthetic hands with electromyography signals, 2019 IEEE International Symposium on Measurement and Control in Robotics (ISMCR), IEEE, 2019, pp. A1-4-1-A1-4-11.
[41] AA. Phinyomark, E. Scheme, Novel Features for EMG Pattern Recognition Based on Higher Order Crossings, 2018 IEEE Life Sciences Conference (LSC), IEEE, 2018, pp. 263-266.
[42] T. Tuncer, S. Dogan, Novel dynamic center based binary and ternary pattern network using M4 pooling for real world voice recognition, Appl. Acoust. 156 (2019) 176–185.