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Automated detection of Parkinson's disease using minimum average maximum tree and singular value decomposition method with vowels

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ABSTRACT

In this study, a novel method to automatically detect Parkinson's disease (PD) using vowels is proposed. A combination of minimum average maximum (MAMa) tree and singular value decomposition (SVD) are used to extract the salient features from the voice signals. A novel feature signal is constructed from 3 levels of MAMa tree in the preprocessing phase. The SVD operator is applied to the constructed signal for feature extraction. Then 50 most distinctive features are selected using relief feature selection technique. Finally, k nearest neighborhood (KNN) with 10-fold cross validation is used for the classification. We have achieved the highest classification accuracy rate of 92.46% using vowels with KNN classifier. The dataset used consists of 3 vowels for each person. To obtain individual results, post processing step is performed and best result of 96.83% is obtained with KNN classifier. The proposed method is ready to be tested with huge database and can aid the neurologists in the diagnosis of PD using vowels.

1. Introduction

Parkinson's disease (PD) is one of the most commonly seen disease worldwide [1,2]. According to world health organization (WHO), 7–10 million people suffer from PD [3–5]. Dopamine is responsible for transmitting signals between the neurons of brain to ensure the smooth and harmonious maintenance of human movements in our bodies. Dopamine-producing cells are present in certain regions of the human brain. These cells are particularly dense in the substantia nigra region of the brain [6–8]. The symptoms of PD occur when these cells are under-operated or damaged. PD is a progressive type of nervous system problem [9]. Muscular tremor, stiffness and deceleration of movements occur because of damaged dopamine production [10–12]. It usually begins by affecting one side of the body and can be seen on the other side over

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time. Common symptoms are muscle tremors while at rest, bending in body posture, numbness, tingling and pain in the limbs, decrease in smell perception, sleep disturbances, constipation and slow movements [13–18].

This disease is progressive and affects the quality of life negatively. Therefore, the early diagnosis of PD is very important for patients [18,19]. The most common symptom is sharking of limbs and hands or fingers. Therefore, early diagnosis is difficult because the symptoms of this disease may vary from person to person. Hence, in this paper the computer-aided diagnosis (CAD) of PD is proposed [20–23] using vowels. In CAD systems, many artificial intelligence, signal processing and machine learning based methods have been presented [22,24–27]. The main objective of these methods is to diagnose PD with high accuracy using physiological signals [21]. The CAD systems developed for PD using electroencephalogram (EEG), gait and vocal signals are shown in Table 1.

As seen in Table 1, vowels, biological makers, EEGs, images, gait signals and surface electromyography (sEMG) signals have been used to diagnose PD. Also, machine learning and deep learning methods have been employed for automated PD diagnosis. Accuracy (Acc) and area under curve (AUC) are used to evaluate the performance of these CAD systems. It can be noted from Table 1 that, biological makers and gait signals have performed better for the diagnosis of PD. In this work, we have used small dataset to obtain high performance using novel MAMa tree method. The motivation of the proposed MAMa tree based method is to recognize PD's with high classification accuracy. We used a small dataset in this article. The major problem of the dataset is small. Hence, high success rates cannot be achieved by using the conventional machine learning methods. Therefore, MAMa tree is presented as preprocessing. Briefly, to solve the problems of the small dataset, a novel solution is presented. The main characteristics of the proposed method are given as below:

- The MAMa tree is applied on the original signal to extract the features. Then, signal and all nodes of MAMa tree are concatenated to construct feature signal during the preprocessing.
- Block based singular value decomposition (SVD) is applied on the feature signal. The maximum singular value of each block is considered as feature.
- In the feature extraction phase, 122 features are extracted and 50 are selected as most distinctive features by using relief.
- 8 classifiers are used in the classification phase.

The major contributions of the proposed method are the use of novel MAMa tree using minimum, average and maximum pooling together. This tree is utilized for preprocessing and used for deep feature extraction (Fig. 1).

As seen in Fig. 1, M, A and Ma represent minimum, average and maximum pooled signals, respectively. The contributions of the proposed method are given in below:

- The pooling methods have been widely used in the deep learning methods especially in convolutional neural networks (CNNs). To extract distinctive features, a multiple pooling method MAMa tree is proposed.

Table 1 – CAD systems developed for detection of PD.

Authors	Methods	Signal type	Results
Sakar et al. [28]	Mel frequency cepstral coefficient, Tunable Q wavelet transform	Vowel signal	Acc: 0.86
Yuvaraj et al. [20]	Alpha, beta, gamma, delta, theta frequency band correlation, coherence phase synchronization index and bispectrum-based phase synchronization index	EEG	Acc: 0.62 Acc: 0.63 Acc: 0.71 Acc: 0.73
Joshi et al. [29]	Wavelet analysis + support vector machine	Gait	Acc: 0.90
Bhat et al. [21]	Machine learning methods	Biological makers	–
Mostafa et al. [11]	Decision tree, naïve bayes, neural network, random forest and support vector machine	Voice	Acc: 0.86 Acc: 0.74 Acc: 0.88 Acc: 0.87 Acc: 0.86
Gottapu and Dagli [30]	Parkinson NET (convolutional neural network + long short-term memory)	Signals + neuro images	–
Lacy et al. [31]	Deep learning (echo state networks)	sEMG	AUC: 0.85
Cigdem et al. [32]	Gray matter + white matter + support vector machine	MRI	Acc: 0.94
Zeng et al. [33]	Ground reaction + support vector machine with radial basis	Gait	Acc: 0.96
Loconsole et al. [24]	Handwriting feature extraction + artificial neural network + support vector machine	sEMG	Acc: 0.93
Han et al. [34]	AR Burg method + wavelet packet entropy	EEG	–
Yuvaraj et al. [23]	Higher-order spectra + machine learning algorithms	EEG	Acc: 0.99
Oh et al. [22]	Convolutional neural network	EEG	Acc: 0.85
Afonso et al. [35]	Convolutional neural network	Handwriting signals	Acc: 0.88
Rios-Urrego et al. [36]	Kinematic, geometrical and non-linear dynamics analyses	Handwriting signals	Acc: 0.84
Sharma et al. [15]	Gray wolf optimization	Handwriting, speech and voice signals	Acc: 0.92 Acc: 0.93 Acc: 0.94 Acc: 1.0

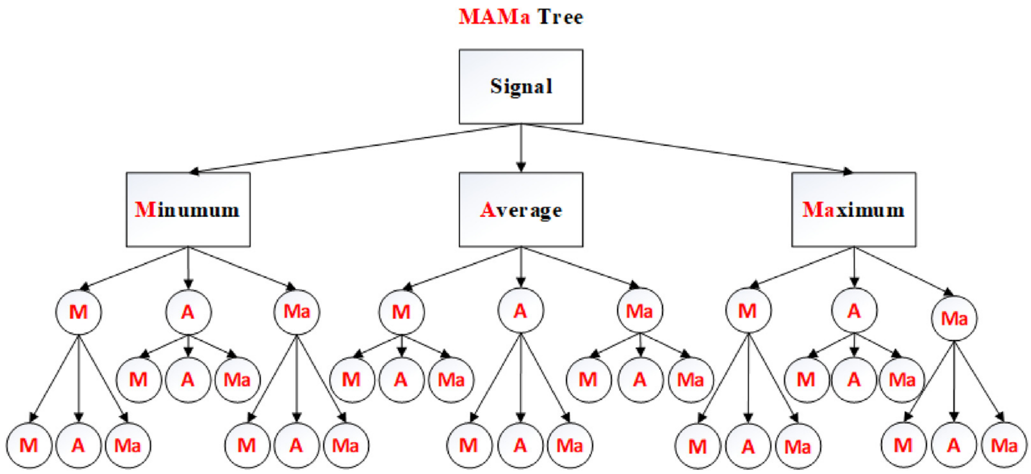


Fig. 1 – Illustration of working of MAMa tree.

- The conventional machine learning methods are used to extract distinctive features.
- The developed model is computationally less rigorous and hence can detect PD automatically in short execution time.
- Fusion of deep learning operators (pooling) and classical machine learning methods (SVD and traditional classifiers) are employed in this work to get high performance.
- The proposed method outperformed the rest of the published works.

2. Materials

In this study, dataset consisting of 756 signals belonging to 252 people were used. The signals were collected from a microphone during examination. The people said "a" vowel three times and these vowels were collected at 44.1 KHz. The attributes of this dataset are given in Table 2.

3. The proposed deep feature extraction network based signal classification method

The proposed method consists of preprocessing, feature extraction, feature selection and classification stages. The graphical outline of the proposed method is shown in Fig. 2.

Table 2 – The details of the dataset used.

Parameters	Values
Number of vowel signal	756
Number of people	252
Number of healthy people	64 (23 men and 41 women)
Number of Parkinson's disease people	188 (107 men and 81 women)
Age range of the healthy people	[33, 87] years
Age range of the Parkinson's disease people	[41, 82] years

3.1. *Preprocessing*

In this stage, MAMa tree is applied to voxel signal to generate novel feature signal [37,38]. The steps of the preprocessing stage are given as below:

Step 1: Load voxel signal.

Step 2: Construct MAMa tree using minimum, average, maximum pooling functions together and Eqs. (1)–(13). The minimum, average and maximum functions are called as MAMa function and pseudo code is shown in Algorithm 1.

Algorithm 1. Pseudo code for MAMa function.

Input: Concatenated signal S with length of L.
Output: Minimum S_{min}, average S_a and maximum S_{max} signals with length of $\frac{L}{2}$.

$r = 1$; // This variable is counter.
for i = 1 **to** L step by 2 **do**
    $window = S(i{:}i+1)$; // Divide signal into non-overlapping windows with length of 2
    $S_{min}(r) = \min(window)$; // min(.) is minimum function.
    $S_a(r) = \mathrm{mean}(window)$; // mean(.) is average function.
    $S_{max}(r) = \max(window)$; // max(.) is maximum function
    $r = r + 1$;
end for i

Step 3: Create 3 level MAM tree using MAM function. The mathematical definition is given below:

$$[S^1S^2S^3] = MAMa(S) \tag{1}$$

$$[S^4S^5S^6] = MAMa(S^1) \tag{2}$$

$$[S^7S^8S^9] = MAMa(S^2) \tag{3}$$

$$[S^{10}S^{11}S^{12}] = MAMa(S^3) \tag{4}$$

$$[S^{13}S^{14}S^{15}] = MAMa(S^4) \tag{5}$$

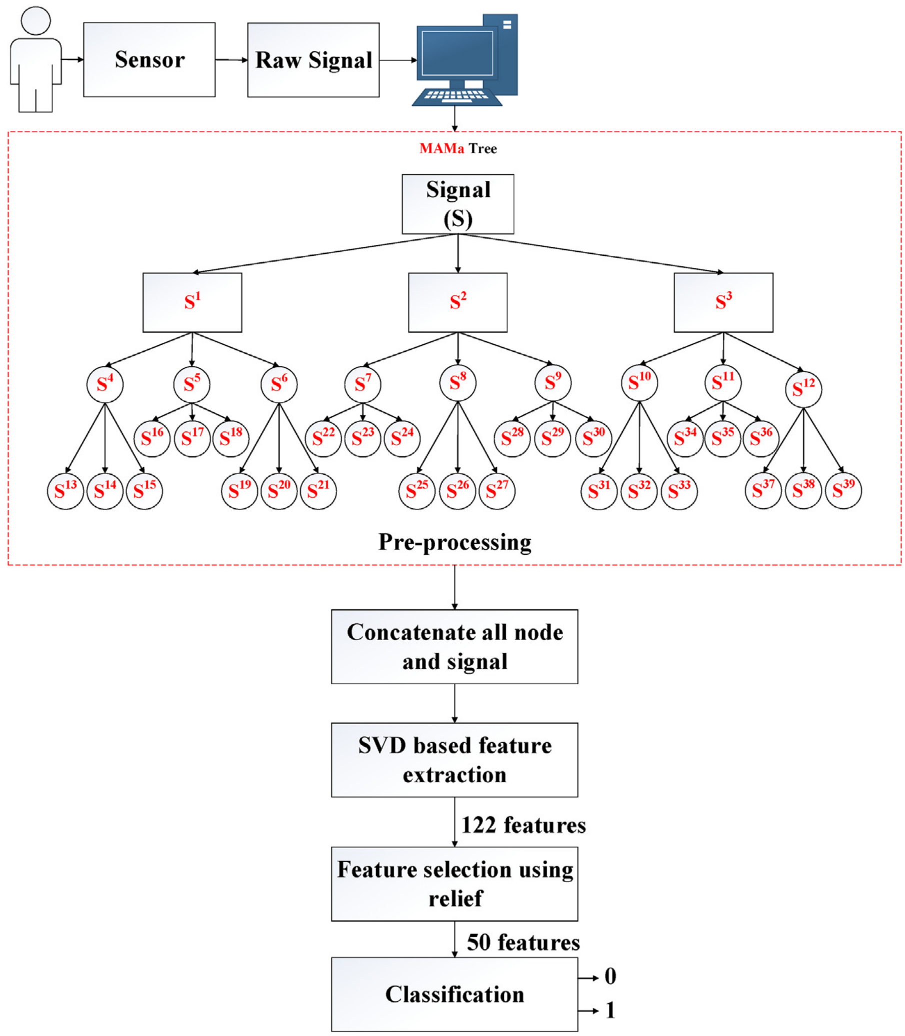


Fig. 2 – The block diagram of the proposed method.

$$[S^{16}S^{17}S^{18}] = MAMa(S^{5}) \quad (6)$$

$$[S^{19}S^{20}S^{21}] = MAMa(S^{6}) \quad (7)$$

$$[S^{22}S^{23}S^{24}] = MAMa(S^{7}) \quad (8)$$

$$[S^{25}S^{26}S^{27}] = MAMa(S^{8}) \quad (9)$$

$$[S^{28}S^{29}S^{30}] = MAMa(S^{9}) \quad (10)$$

$$[S^{31}S^{32}S^{33}] = MAMa(S^{10}) \quad (11)$$

$$[S^{34}S^{35}S^{36}] = MAMa(S^{11}) \quad (12)$$

$$[S^{37}S^{38}S^{39}] = MAMa(S^{12}) \quad (13)$$

where $MAMa(.)$ is MAMa function and $S^1, S^2, \ldots, S^{39}$ are nodes of the MAMa tree.

Step 4: Concatenate all nodes of MAMa tree to obtain the feature signal.

$$fS = Conc(S, S_1, \ldots, S_{39}) \quad (14)$$

where fS is feature signal with length of $L + (3L/2) + (9L/4) + (27L/8) = 65L/8$.

3.2. *Feature extraction*

The SVD is used for matrix factorization [39–42]. The SVD is generally used in search engines, feature extraction, image decomposition, and perceptual hash generation. The SVD calculates *three* factors of a matrix and these are called as diagonal (U), singular (S) and vertical (V). SVD is used in the feature extraction stage. First, the feature signal is divided into 50 sizes of non-overlapping windows. Then, each window is reshaped to 5 × 10 block sizes and SVD is applied on each block. Finally, the maximum singular value of each block is assigned as feature. The pseudo code of the proposed feature extraction method is shown in Algorithm 2:

Algorithm 2. The pseudo code of the proposed SVD based feature extraction method.

Input: Concatenated signal *fS* with length of $\frac{65L}{8}$.
Output: Feature *feat* with length of $\lfloor \frac{65L/8}{50} \rfloor = \lfloor \frac{65L}{400} \rfloor$.

```
r = 1; // This variable is counter.
for i = 1 to 65L/8. step by 50 do
    window = fS(i:i + 49); // Divide signal into 50 sizes non-overlapping window.
    block = reshape (windows, 5 × 10) // Reshape window to 5 × 10 sizes block.
    [U S V] = SVD (block); // Apply SVD to block
    feat(r) = max(S); // Memorize maximum singular value as feature.
    r = r + 1;
end for i
```

The MAMa signal is divided into 50 non-overlapping blocks yielding 122 features.

3.3. *Feature selection*

We have used relief-based feature selection method. In this work, we have chosen 50 most significant features using relief [43–45]. We tested the proposed method using variable number of features and the best results were obtained using 50 features.

Fig. 3 illustrates various steps involved in our proposed method.

3.4. *Classification*

Eight classifiers namely: linear discriminant (LD), support vector machine (SVM) with linear, radial based function (RBF) kernel, and cubic kernel are used. Logistic regression (Log-Reg), k nearest neighborhood (KNN) with city block distance and $k = 1$, and bagged tree (BT) are used. We have used classification learner tool of the MATLAB 2018a. There are 23 classifiers in the classification learner toolbox. Among them eight classifiers with 10-fold cross validation strategy yielded the highest classification performance. Hence, we have chosen the best performing eight classifiers in this work.

3.5. *Post processing*

To obtain individual results, the post processing used predicted signals and Algorithm 3. In the classification phase, we have obtained predicted signals and there are 3 signals for each person. A simple algorithm is applied onto the predicted 3 signals. The pseudo code used for the individual result calculation is given in Algorithm 3:

Algorithm 3. Pseudo code for individual result calculation.

Input: Predicted results (*PR*) with size of 756.
Output: Individual results (*IR*) with size of 252.

```
c = 1; // This variable is counter.
for i = 1 to 756 step by 3 do
    result = mean(PR(i:i + 2)); // Calculate average predicted value for each person
    if result ≥ 0.67 then // The generalization of the truth table.
        IR(c) = 1; // PD
    else
        IR(c) = 0; // Healthy
    end if
    c = c + 1;
end for i
```

In order to better understand the post processing step, the truth table of post processing is given (Table 3).

For instance, if 2 vowels of a person are PD and 1 vowel is healthy, this person is considered as PD according to our post processing step.

In case 1, 756 vowels are classified and 252 people are classified using post processing in case 2.

Case 1 used preprocessing, feature extraction and classification steps. Case 2 used preprocessing, feature extraction, classification and post processing steps.

4. Performance analysis and discussion

To test the performance of the proposed method, classification capability, and execution time are used. To evaluate the proposed method comprehensively, 8 items are defined and they are given below. In Sakar et al.'s method, many classifiers were used to obtain a comprehensive benchmark. Hence, 8 classifiers are used in this work. 50 most distinctive features are selected using relief and the parameters used for the classifiers are given as below:

Item 1: For LD classifier: we have used full covariance structure.

Item 2: In SVM with linear kernel: we have chosen box constraint level = 1, kernel scale mode is auto and multiclass method is one-vs-one.

Item 3: In SVM with radial basis function (RBF) kernel: we have selected box constraint level = 1, kernel scale mode is auto and multiclass method is one-vs-one.

Item 4: In SVM with cubic kernel classifier: we have adopted box constraint level = 1, kernel scale mode is auto and multiclass method is one-vs-one.

Item 5: In Log-Reg classifier: There is no parameter tuning was done.

Item 6: In KNN classifier: $k = 1$ and distance metric of city block are selected.

Item 7: For decision tree classifier: we have used maximum number of splits = 20 and split criterion = Gini's diversity index.

Item 8: For BT classifier: we chose ensemble method of bag, learner type = decision tree, maximum number of splits = 755 and number of learners = 30.

In order to obtain numerical results from these items, accuracy, precision, recall and F-measure are used. Mathematical definitions of these parameters are given in Eqs. (15)–(18):

$$acc = \frac{TP + FP}{TP + FP + TN + FN} \quad (15)$$

$$P = \frac{TP}{TP + FP} \quad (16)$$

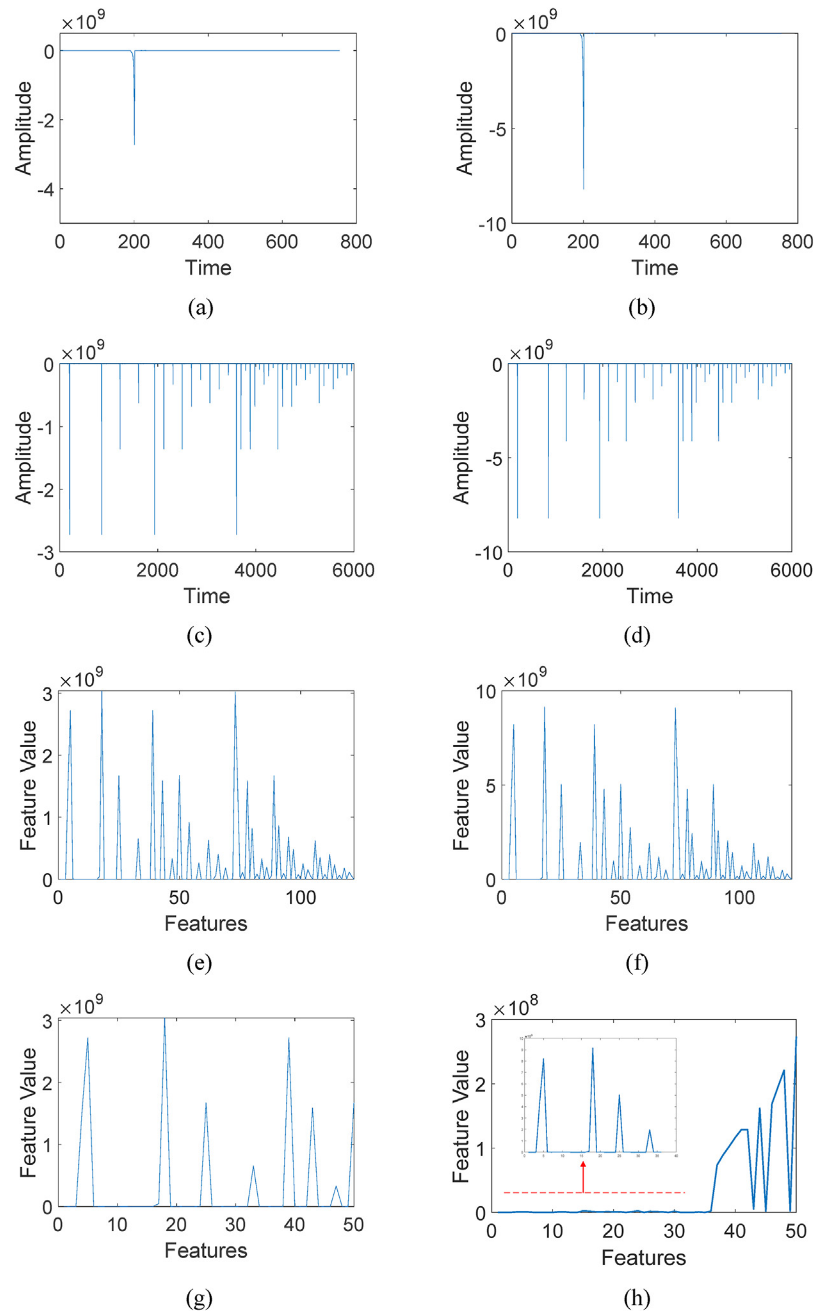


Fig. 3 – Illustration of the proposed method: (a) raw signal of PD subject; (b) raw signal of healthy subject; (c) preprocessed signal of PD subject using MAMa tree; (d) preprocessed signal of healthy subject using MAMa tree; (e) feature signal of PD subject; (f) feature signal of healthy subject; (g) selected 50 distinctive features of PD subject; (h) selected 50 distinctive features of healthy subject.

$$R = \frac{TP}{TP + FN} \quad (17)$$

$$F1 = 2\frac{P * R}{P + R} \quad (18)$$

where TP, FP, TN and FN are true positives, false positives, true negatives and false negatives, respectively. acc is accuracy, P is precision, R describes recall and $F1$ is F-score.

The obtained results for the proposed items are listed in Table 4. These evaluation parameters have been widely used in machine learning [46,47]. Hence, we used these metrics to compare the proposed method with other works.

In Table 4, the training results of the vowels are listed. To obtain the individual results for the proposed method, the predicted vowels and post processing step are used together. The results for the individual cases are listed in Table 5.

Table 3 – Truth table of post processing.

Predicted 1st signal	Predicted 2nd signal	Predicted 3rd signal	Individual result
Healthy	Healthy	Healthy	Healthy
Healthy	Healthy	PD	Healthy
Healthy	PD	Healthy	Healthy
Healthy	PD	PD	PD
PD	Healthy	Healthy	Healthy
PD	Healthy	PD	PD
PD	PD	Healthy	PD
PD	PD	PD	PD

4–7 lines of the Algorithm 2 express truth table of post processing.

Table 4 – Results obtained for various classifiers (items) using 756 vowels (case 1).

Item number	Accuracy	Precision	Recall	F1
Item 1	0.8413	0.8114	0.7414	0.7754
Item 2	0.8360	0.8741	0.6925	0.7693
Item 3	0.8452	0.8644	0.7757	0.8177
Item 4	0.8902	0.8548	0.8560	0.8554
Item 5	0.8360	0.7653	0.7927	0.7788
Item 6	**0.9246**	**0.9000**	**0.9014**	**0.9007**
Item 7	0.8056	0.7543	0.6876	0.7194
Item 8	0.8717	0.8517	0.7938	0.8217
Average	0.8563	0.8345	0.7801	0.8048

Table 5 – The best results obtained for individual cases (252 people) (case 2).

Item number	Accuracy	Precision	Recall	F1
Item 1	0.8452	0.8236	0.7574	0.7805
Item 2	0.8373	0.8556	0.6795	0.7574
Item 3	0.8730	0.8780	0.7837	0.8282
Item 4	0.9484	0.9349	0.9164	0.9256
Item 5	0.8532	0.8278	0.7625	0.7938
Item 6	**0.9683**	**0.9677**	**0.9478**	**0.9577**
Item 7	0.8135	0.7707	0.6946	0.7307
Item 8	0.8929	0.8693	0.8147	0.8411
Average	0.8789	0.8659	0.7945	0.8268

In Table 5, the best classification accuracies are listed for case 2. Each item is repeated by 100 times and the average accuracy rates and their standard deviations are listed in Table 6.

According to results, the best item is Item 6 and the best classifier is 1NN. Also, the proposed method is compared with the work by Sakar et al. [28]. In their method, they used KNN, Log-Reg, linear SVM and RBF SVM classifiers. They achieved the best results using RBF–SVM. Table 7 provides the comparison results of the proposed method with Sakar et al.'s method using accuracy and *F*-measure. F1 score represents individual success rates for each class. Hence, it has been widely used to evaluate the performance of machine learning methods [28]. To compare the performance of various methods, accuracy and F1 are used and obtained results are listed in Table 7.

It can be seen from Table 7 that the best accuracy rate of the proposed method is 6% higher than Sakar et al.'s method. Also, the best individual result is 10% higher than Sakar et al.'s method. The higher success rates than Sakar et al.'s method are highlighted with bold text font.

The execution time of the proposed method is computed for better evaluation. Our personal computer (PC) with 16 GB RAM and Intel i7-7700 CPU having 3.60 GHz was used for this work. The operating system of this PC is Windows 10.1 and MATLAB 2018a was used to implement this method. We executed this method using MATLAB2018a 100 times and the average execution time is 4.14 s for all items.

The salient characteristics of our proposed method are given as below:

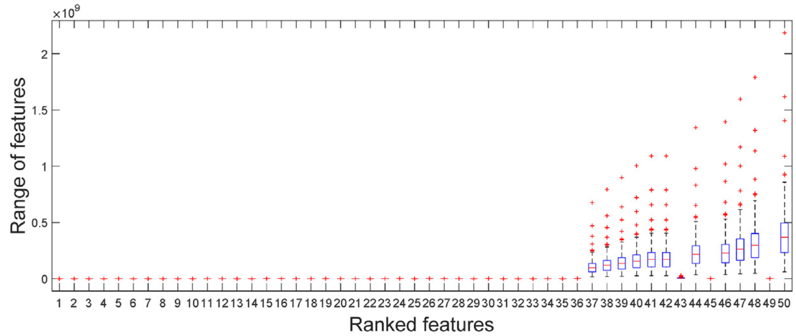
- In this method MAMa tree based preprocessing, feature extraction by SVD, feature selection by relief method and classification are used. Finally, 50 separable features are extracted. The statistical analysis of the features for the *two* classes is shown in Fig. 4.

Table 6 – The average accuracy rates and standard deviation of individual cases (252 people; case 2).

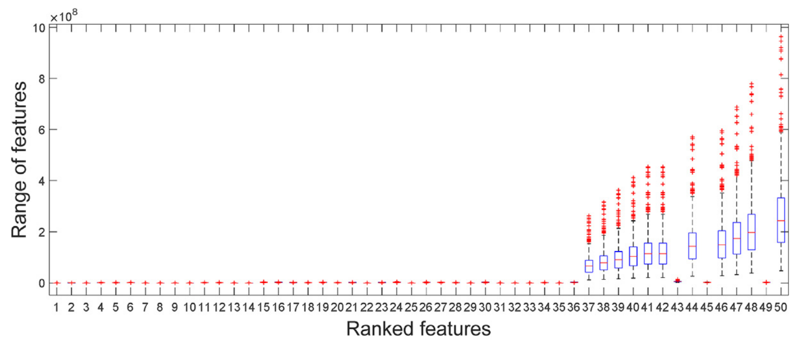
Items	Accuracy
Item 1	0.8438 ± 0.0067
Item 2	0.8296 ± 0.0012
Item 3	0.8810 ± 0.0041
Item 4	0.9444 ± 0.0051
Item 5	0.8511 ± 0.0041
Item 6	**0.9591 ± 0.0033**
Item 7	0.8066 ± 0.0055
Item 8	0.8811 ± 0.0081

Table 7 – Comparison results of the proposed method with Sakar et al.'s method using accuracy and *F*-measure.

Classifier	Sakar et al.'s method		The proposed method (signal classification results) (case 1)		The individual result of the proposed method (case 2)	
	Accuracy	F1	Accuracy	F1	Accuracy	F1
KNN	0.84	0.83	**0.92**	0.90	**0.97**	**0.96**
Linear SVM	0.83	0.82	**0.84**	0.82	**0.84**	**0.76**
RBF SVM	0.86	0.84	0.85	0.78	**0.87**	0.83
Log-Reg	0.85	0.84	0.84	0.78	0.85	0.79



(a) Features obtained for class 0 (normal).



(b) Features obtained for class 1 (PD).

Fig. 4 – The box plots of features for two classes: (a) normal; (b) PD.

Fig. 4 shows the box plots for the first 50 features for the two classes. It can be noted from the figure that feature values are higher for normal class (Class 0) as compared to the PD class (Class 1). These features are distinct for *two* classes and hence, we have obtained high classification performance.

- In order to evaluate the proposed method, 8 items (classifiers) are used. These items are used to evaluate comprehensively the proposed method and obtain the comparisons. We have used 23 classifiers of the MATLAB classification learner toolbox and the best performance of 8 classifiers is presented in this paper. KNN classifier achieved the best classification accuracy of 92.46%.
- To calculate the individual results, a novel strategy is proposed. This strategy used Algorithm 3 and 96.83% accuracy using this algorithm.
- The area under curve (AUC) is 0.895 for the best classifier (KNN).
- We defined *two* cases to evaluate the performance. The vowels are classified using 10-fold cross validation (case 1) and post processing is used to obtain individual results (case 2).
- The average accuracy rates of vowels and individual results are found to be 85.29% and 87.66%, respectively.
- Computational complexity of the proposed MAMa tree based PD recognition method is calculated as $O(nlogn)$.
- The classification accuracy of our method is approximately 6% higher than the best performing state-of-art method (Sakar et al.). Hence, our proposed MAMa tree method is more effective and accurate in detecting the PD using vowels.

The advantages of the proposed method are:

- Distinctive features are extracted using MAMa tree and SVD method.
- Achieved high classification performance even with heterogeneous dataset.
- Proposed method can be used for real-time healthcare monitoring system of PD as it is computationally less expensive.
- Developed system is cognitive method because any weight updating or meta-heuristic optimization is not used in this method.
- Achieved high classification ability without setting any parameters. Hence, the system is non-parametric.
- Proposed method is simple and easy to use.
- The disadvantage of this study is that, we have used small dataset for this work.

5. Conclusions

In this study, a novel MAMa tree and SVD are used for the automated detection of PD using vowels. The proposed method consists of MAMa tree based preprocessing, feature extraction using SVD, relief-based feature selection and KNN for classification. In this study, we proposed *two* cases with 8 items. In case 1, vowel classification is performed and individual PD classification is done using post processing in case 2. Our proposed method is able to detect the PD using features extracted from the vowels (case 1) with highest classification accuracy of 92.46% and highest individual (case 2) results of 96.83% using KNN classifier. Based on the execution time and computational complexity measurements, we can conclude that, our system is less complex and fast.

Our developed algorithm can be used to analyze other physiological signals like electrocardiogram (ECG), electroencephalogram (EEG), phonocardiogram (PCG), and electromyogram (EMG) to diagnose various other diseases.

Author's contributions

Conception and design of study: Turker Tuncer; acquisition of data: Sengul Dogan; analysis and/or interpretation of data: Turker Tuncer, Sengul Dogan, and Rajendra Acharya; drafting the manuscript: Turker Tuncer and Rajendra Acharya; revising the manuscript critically for important intellectual content: Turker Tuncer, Sengul Dogan, and Rajendra Acharya; approval of the version of the manuscript to be published: Turker Tuncer, Sengul Dogan, and Rajendra Acharya.

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