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Original Article

Cepstral Coefficient Extraction using the MFCC with the Discrete Wavelet Transform for the Parkinson's Disease Diagnosis

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Abstract *- Studies consider Parkinson's disease the second most common neurological syndrome after Alzheimer's. To get an accurate diagnosis, we have recourse to the signal treatment. One of the most used methods in sound recognition and speaker identification is the Mel Frequency Cepstral Coefficients (MFCC). In this technique, the first step is Pre-emphasize the signal, then frame and window it. After that, the Cepstral analysis in which the Fast Fourier Transform (FFT) is applied, followed by the Discrete Cosine Transform (DCT) and the liftering of the Mel Frequency Cepstral Coefficients. This paper proposes to work with the Discrete Wavelet Transform (DWT) instead of the filter bank at the filtering step. Using data containing 17 healthy and 20 patients with Parkinson's, 12 MFCC coefficients will be extracted and classified using the Support Vector Machine (SVM). Thence, a method consisting of inserting DWT into the MFCC bloc will be conducted to compare the result with the previous experience when DWT was outside the MFCC bloc and with the one using only the MFCC without DWT to fetch the accurate process of Parkinson's disease detection.*

Keywords *- Parkinson's disease, MFCC, Daubechies, Wavelet, Filter bank, SVM.*

1. Introduction

The gradual loss of brain cells responsible for dopamine production and storing causes a neurological disorder known as Parkinson's disease (PD), as described by James Parkinson in 1817 [1]. Parkinson's disease affects the coordination of movements, such as the trembling of the upper and lower limbs and the vocal tract. Among the recently proposed biomarkers of Parkinson's disease, vocal analysis was investigated in the following research [2, 3]. Hamid Karimi Rouzbahani et al. [2] work with speech signals from which they extract coefficients and then classify them using several classifiers such as SVM. The satisfactory classification performance is achieved by the lack of need for physician's intervention and implicitly the self-sufficiency of the method. Y. Campos-Roca et al. [3] used MFCC coefficients and an SVM classifier. Their study proved that the PD could be detected with an accuracy of 85% centered on recordings of the sustained vowel /a/.those studies about which recent research has been carried out using the cepstral coefficients of the MFCC [4], Perceptual Linear Prediction (PLP) [4], realized by Achraf Banba et al. while E. Benmalek et al. [5] used different coefficients such as jitter and shimmer extracted from voice, beside the SVM classier, to distinguish between PD patients at different severity stages and healthy people. The paper [6] has created a prediction system for Parkinson's disease centered on speech signals (vowels). B. Nsiri et al. suggest two methods, the first was the Genetic Algorithm (GA) for feature selection embedded with the KNN classifier, and the second was GA-KNN with ensemble learning. The results confirm the results obtained in [3] that the most appropriate vowel for Parkinson's disease detection is the /a/ among the vowels /a/ /o/ /u/. Savitha S. Upadhyaa et al. [7] performed a study based on the extraction of MFCC and PLP by the use of the Thomson window technique multitaper to detect Parkinson's disease. In other work [8], Mrs.Snehal S. Golait et al. have provided a feature extraction for Handwritten Marathi Compound Character using structural (Edge map) and statistical features extraction methods (DFT and DWT). Boualoulou et al. [9] have proposed a treatment centered on testing several kinds of DWT to decompose each voice sample. Then, from the decomposed signal, they extracted the delta MFCC and applied the decision tree as a classifier. Sonali Lohbare et al. [10] proposed an ECG signal de-noising algorithm based on DWT for analyzing, approximating, and detailing The noisy signal. In similar work, Raaed Faleh Hassan et al. [11] extracted the ECG signal common features centered on DWT.

Support Vector Machine (SVM) is one of the most important tools in the machine learning field. The principal is so clear as if teaching a child how to differentiate between two animals (cats and dogs) by showing him pictures of the two animals during the learning phase and then showing him the picture of one animal and asking him what it is. This test phase aims to ensure that the child can say correctly which is which. Mainly support vector machine (SVM) has been reported, so the distinction between the sick affected by varied diseases and healthy people could be fulfilled. B. Magnin et al. [12] used whole-brain anatomical Magnetic Resonance (MR) images and SVM to detect Alzheimer's disease. Also, in a study on SWEDD and Parkinson's disease, five regions were identified by SVM with an accuracy as high as 81.25% [13].

Moreover, SVM was applied in acoustic signals to diagnose respiratory pathologies [12] and Parkinson's disease [14-23]. The paper [16] by T. Belhoussine Drissi et al. used the different sorts of DWT on data containing recordings of people who utter the vowel /a/ to obtain the MFCC coefficients, then classified those coefficients by applying the SVM. In their study, S. Aich et al. [24] proposed the detection of PD among other neurological diseases. They considered two different features selection applying SVM classier.

In this paper, we conceive an alteration in the process of extracting Mel Frequency Cepstral Coefficients, which is the filtering by Discrete Wavelet Transform (DWT) instead of the triangular filter banks. A database [25] containing 17 healthy patients and 20 sick patients will be used to extract 12 cepstral coefficients of each patient and then proceed to differentiate the sick patients from the sound ones by applying the SVM classifier with the training bases created from the database which accounts for 73% of the database. Section 2 of this paper explains the methodology followed in this study. Whereas section 3 represents the data used in this study. Results and discussion are presented in section 4. The conclusion is drawn in section 5.

2. Research Method

2.1. Problem statement

In this study, the applied process aimed to embed the DWT in the MFCC technique. The first phase is the pre-processing of the speech signal following 3 steps: pre-emphasis, segmentation, and windowing. The cepstrum analysis is applied with the DWT that replaces the filter bank for filtering. In the end, a classification is executed using the SVM classifier.

The MFCC is a technique of feature extraction. This technique was suggested by Bridle and Brown in 1947 and then developed by Mermelstein in 1976 [26]. In the MFCC, the property of the human ear is used to receive frequencies less than 1 kHz at a linear scale, while frequencies higher than 1 kHz are received at a logarithmic scale. The coefficients extraction process used in previous works is as follows in Fig. 1(a) [15].

In a previous paper [16], a new Parkinson's disease detection method was adopted. This method has been based on transforming the speech signal by the DWT before extracting the MFCC's coefficients, as illustrated in Figure 1(b). After the signal transformation, the approximation a3 of each DWT will be used as the input of the MFCC extraction block (12 coefficients for each patient).

2.2. Proposed method

The cepstral analysis was proposed to isolate the convolution between the vocal tract and the excitation source, which is a product that makes it difficult to separate. In speech automatic recognition, Mel scale cepstral coefficients (MFCC - Mel Frequency Cepstral Coefficients) constitute an extensive characterization tool. These coefficients are derived from the power spectrum in applying a filter bank uniformly spaced on a modified frequency scale called the Mel scale, which is designed according to the perceptual criteria of the human ear. An analysis filter bank decomposes signals into low and high pass components. Usually, this step of filtering is applied by using the filter bank. In this paper, we propose to conduct the filtring via a wavelet filtering technique, namely the Discrete Wavelet Transform (DWT). The process of extracting the coefficients will be altered in Fig. 1(c).

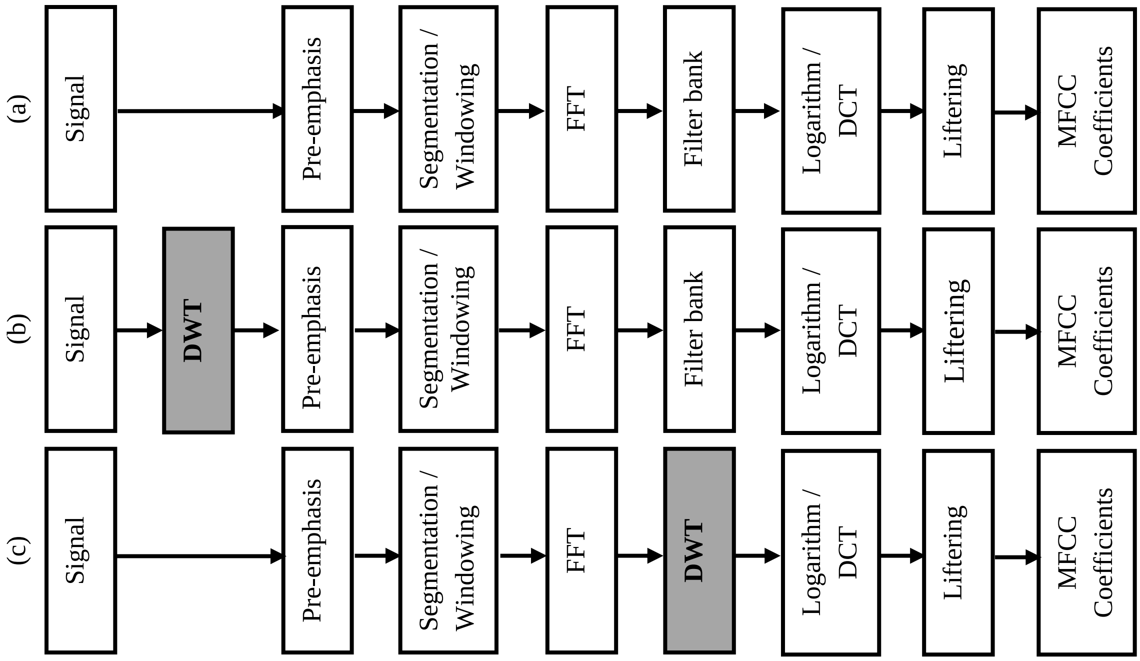

Fig. 1 On the right: is the process of extracting the coefficients. On the left: is the new process of extracting the coefficients

In this technique, a first-order finite impulse response digital filter given in the equation below is used to accentuate the signal's high frequencies.

$$H(z) = 1 - k\, z^{-1} \tag{1}$$

This article's pre-emphasis coefficient k is experimentally set at 0.97 [16].

As it is known, the signals used in the signal processing methods are stationary. In contrast, the audio signal is non-stationary, so that the signal will be segmented into frames of N speech samples at 10 to 30 ms intervals. The hamming window reduces the discontinuities shown as a consequence of the framing at the ends of each frame. Each frame is multiplied by the hamming:

$$s_n'' = \left\{0{,}54 - 0{,}46\cos\left(\frac{2\pi n}{N-1}\right)\right\} s_n' \tag{2}$$

The FFT aims to convert the speech signal from the time domain to the frequency domain.

The MFCC coefficients are calculated from the Fast Fourier transform (FFT) coefficients, filtering each frame of N samples from the time domain into the frequency domain, filtered using a discrete wavelet transform.

In the lifting phase, as depicted in Fig. 1(c), the use of DWT was suggested instead of the filter bank. The WT has been developed to overcome short-term Fourier Transform (STFT) resolution defects. It can provide a simultaneous time-frequency representation of the signal. For the STFT method, the time signal passes through various high pass and low pass filters that filter the high and low-frequency parts of the signal. We cannot know exactly which component spectral exists at a given moment, so looking for what spectral components exist over a given time interval is the best that could be done. It's a resolution problem, which is why researchers went from STFT to WT. Indeed, the STFT gives a fixed resolution for all moments while the WT gives a resolution variable.

The algorithm of the DWT is based on the definition of a pair of filters G (high pass filter) and H (low pass filter), as shown in Fig. 2. The filter outputs are sub-sampled by a factor of 2. The low-pass filter gives the approximation coefficients ai of the signal at the same scale. The high-pass filter provides signal details or Discrete Wavelet Decomposition coefficients d_i at a given scale. This paper will use the Daubechies wavelet at level 2 and the scale 3, which gives the best results in previous works [15]. Where Mel(f) is the logarithmic scale of the normal frequency scale f., the discrete cosine transform will convert the Mel(f) to time to obtain MFCCs:

$$c_i = \sqrt{\frac{2}{N}} \sum_{j=1}^{M} a_3 \cos\left(\frac{\pi i}{N}(j - 0{,}5)\right) \tag{3}$$

Here a3 is the logarithm of the energy obtained with the discrete wavelet transform, and M is the length of the vector a3.

To overcome the problem of the higher order of the cepstral coefficients being too small, the liftering will be applied to lift the cepstrum. As a consequence, so that the amplitudes become quite similar, it is important to increase them [15]. So the cepstral coefficient will be lifted according to the following equation:

$$c_n' = \left(1 + \frac{L}{2}\sin\left(\frac{\pi n}{L}\right)\right)c_n \qquad (4)$$

Where L is the Cepstral sine lifter parameter. In this study the value used is L = 22 [14], [16].

In the last phase, the classification, the SVM, was used. The main idea of SVM is to project the data into a space of the largest dimension called the "space of features" so that the data not linearly separable airspace in the entrance space becomes selectively separable in the space of features. By applying the technique of constructing an optimal hyperplane separating the two classes in this space, we obtain a classification function that depends on a scalar product of the images of the data and the space of entry into the features. This scalar product can be expressed under certain conditions by functions denoted in the entry space, called nuclei. This multiple-choice of cores makes the SVM more interesting and especially richer since it always allows us to look for new kernels that may be better suited to the task one wants to accomplish. Fig. 3 below shows the SVM technique Principe.

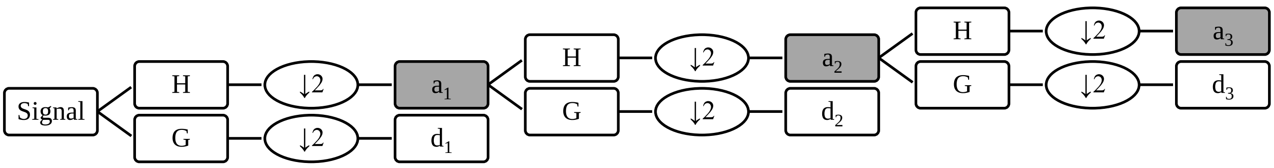

Fig. 2 Multi-resolution analysis at 3 levels of scales (ai: approximations and di: details).

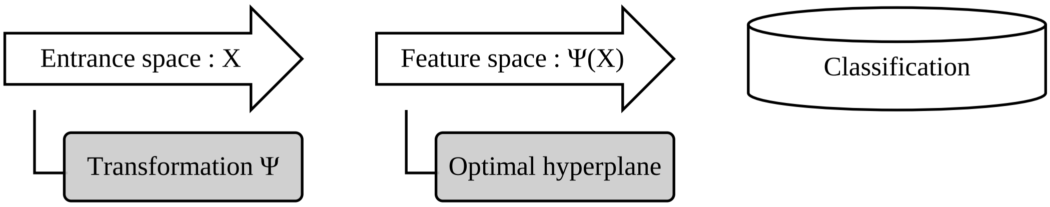

Fig. 3 Principe of SVM technique.

The algorithm below describes the steps followed in this study.

Algorithm
Initialization: Tw is the sampling rate (25 ms). K is a pre-emphasis coefficient (0.97). L is the cepstral sine lifter parameter. M is the maximum of the wavelet scale. 1 For all the audios: 2 Read the recorded audio of the patient, and convert it to a signal. 3 Call a function that has the output signal of the filter as input. This function put the signal into frames and then multiplied the frames by Hamming window. 4 Calculate the Magnitude spectrum computation, which is the absolute value of the FFT output. 5 Extract the vector composed of a_m, d_m, d_{m-1}, …,d_1 applying the DWT. 6 Applied equation 4 with the am as input. 7 Calculate the log, and lift the coefficients. 8 Output: features matrix in which each column represents a coefficient, and a row represents a patient. 9 Create the training model with 73% of the features matrix. 10 Do the test with the whole matrix. 11 The results of sick and healthy patients.

3. Dataset

The database [25] will be based on classifying the healthy and sick ones. This data is composed of 37 voice records. In this record, 17 healthy and 20 sick patients were asked to utter the vowel /a/ three times. The microphone used was standard with 44.100 Hz as sampling frequency while using the sound card of 16-bit in a desktop computer. The program followed in this classification system was executed in Matlab 2014a. The latter was installed in a laptop with Intel_ Core TM i3-5005U CPU (2.00 GHz, 4 CPUs) and 4 Go RAM.

4. Results and Discussion

This paper wants to follow an approach centered on two phases: the coefficients extraction phase in which seeking to extract MFCCs after the operation of the pre-emphasis, framing, and windowing comes the step of cepstral analysis in which FFT is applied, then the triangular filter banks usually used will be altered by the discrete wavelet transform. The next step is calculating the logarithm of the approximation a3, then applying the DCT transform before liftering. Hence, extracting each patient's first 12 MFCC coefficients using the program "Htk mfcc Matlab" [27]. Relying on these coefficients as characteristics to make a classification (have a correct diagnosis). The large number of frames that MFCC contains prevents an accurate diagnosis because it requires significant processing time for classification [16]. The average value of these images will be calculated to get the voiceprint to cope with the previous problem.

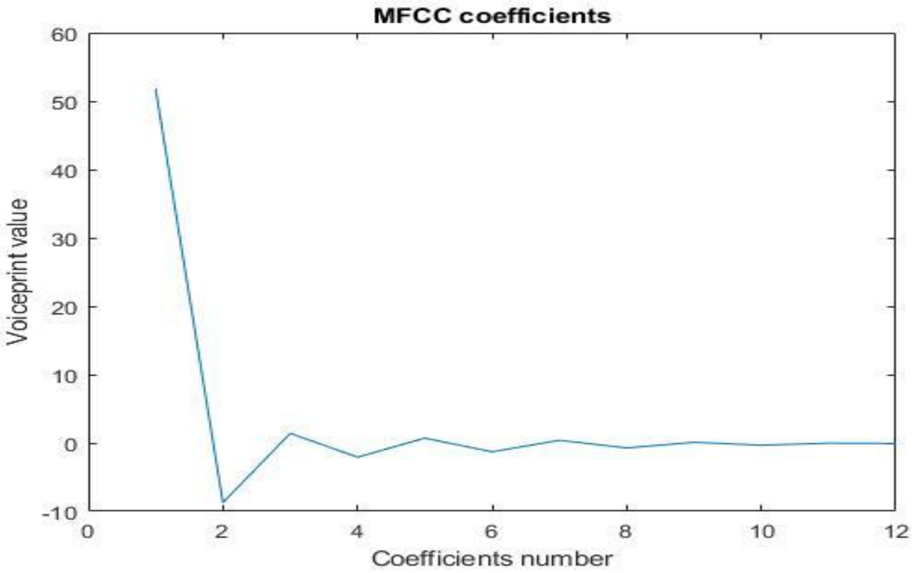

Fig. 4 The average of MFCC coefficients is obtained by the process in figure 1(a).

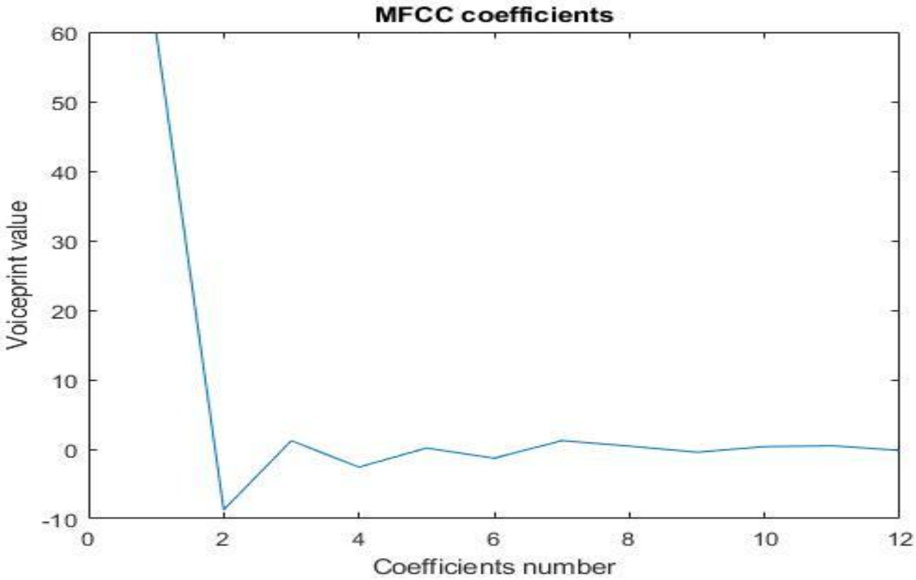

Fig. 5 The average of MFCC coefficients is obtained by the process in figure 1(b).

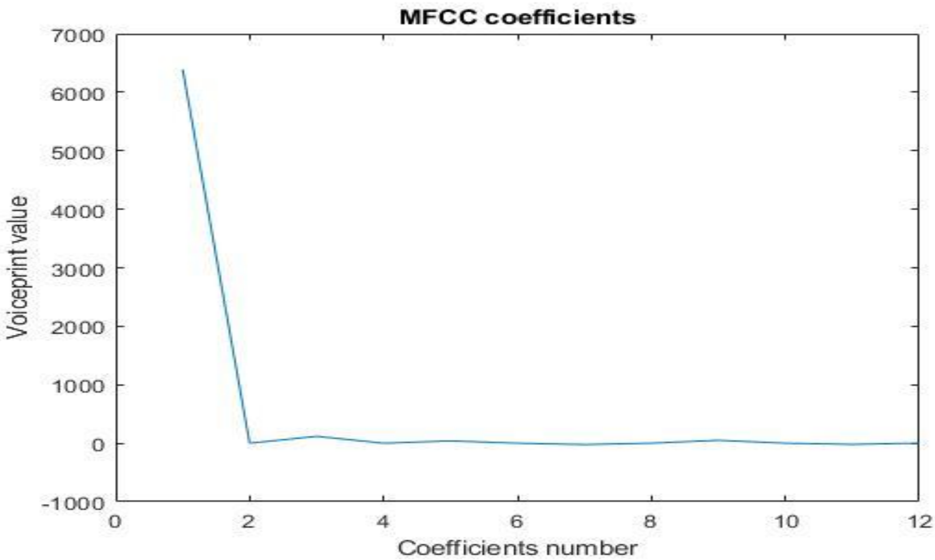

Fig. 6 The average of MFCC coefficients is obtained by the process in figure 1(c).

The figures below give the 12 MFCC coefficients extracted using different methods for a Parkinson's patient.

Fig. 4 presents the process (a) directed in Fig. 1(a), in which the extraction of MFCC has been applied without the use of DWT. In Fig. 5, the extraction was done after using the DWT to transform the speech signal. While in Fig. 6, we propose to use the DWT instead of the Filter bank in the MFCC bloc.

The classification phase (second phase) aims at classifying sound and sick patients. So as a first step to achieving this goal, a training base that accounts for 73% of the database will be created. Then the diagnostic test on the whole database will be applied. The classification process is explained in Fig. 7.

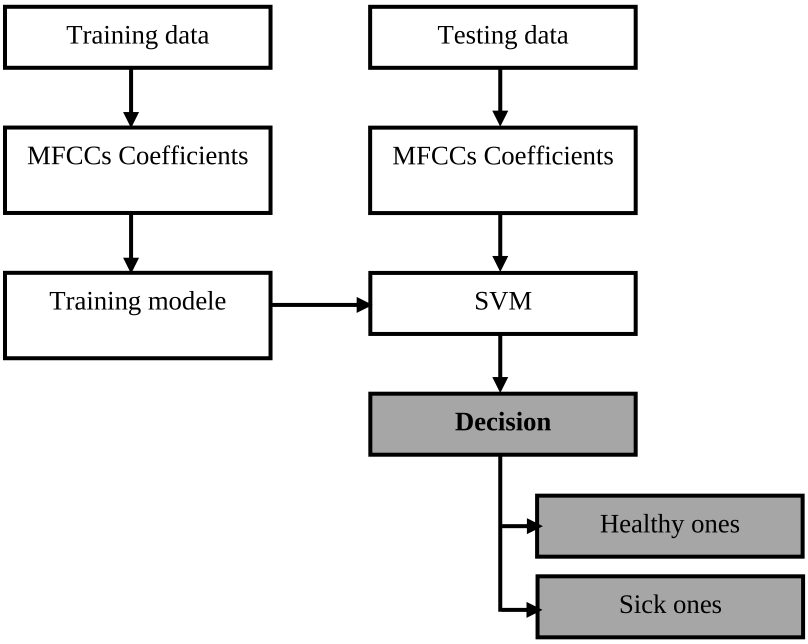

Fig. 7 The Prediction of Parkinson's Disease Principe.

Aiming to pursue the classifier's performance, we recourse to crucial measures: accuracy, sensitivity, and specificity. The calculation of those measures is effected according to the following formula in [16]:

$$\text{Accuracy} = \frac{VN + VP}{FP + FN + VP + VN} \quad (5)$$

$$\text{Specificity} = \frac{VN}{FP + VP} \quad (6)$$

$$\text{Sensitivity} = \frac{VP}{FN + VP} \quad (7)$$

Whereas :

- VN stands for a true negative (Parkinson's patients correctly detected).
- VP stands for a true positive (sound patients correctly detected).
- FN stands for a false negative (sound patients misclassified).
- FP stands for a false positive (Parkinson's patients misclassified).

Percentage calculation of accuracy, sensitivity, and specificity of all the recordings from the training base that was created between the MFCC block output and the input of the SVM block by using the training base of 73% for the db1, db2, db3, and db4 at the first 5 scales of each level are given in the following Table 1. Fig. 4 depicts the classification strategy based on 2 phases of training to create the model and then the phase of testing the data in which a decision will be made.

Table. The classification results using the DWT instead of the filter bank with kernel SVM.

	Accuracy (%)				**Sensitivity (%)**				**Specificity (%)**			
wavelet / Scale	db1	db2	db3	db4	db1	db2	db3	db4	db1	db2	db3	db4
1	72.97	73,64	70,94	72.29	82,35	82,35	85,29	80,88	65	77,5	68,75	66,25
2	72.97	79,05	78,37	81,08	76,47	86,76	86,76	92,64	70	81,25	73,75	75,00
3	81,08	79,73	**81,75**	81,08	89,70	88,23	89,70	91,17	100	78,75	80,00	77,5
4	81,08	79,73	80,40	81,08	86,76	86,76	86,76	88,23	77,5	80,00	80,00	78,75
5	79,73	79,73	78,37	80,40	88,23	86,76	94,11	88,23	77,5	80,00	78,75	78,75

Table 2. The classification results using the DWT before the MFCC bloc [22]

	Sensitivity (%)			Sensitivity (%)			Specificity (%)		
wavelet / Scale	db1	db2	db3	db1	db2	db3	db1	db2	db3
1	28.95	76.32	73.68	33.33	83.33	83.33	25	70	65
2	65.79	78.95	76.32	55.56	77.78	77.78	75	80	75
3	84.21	**86.84**	78.95	94.44	94.44	94.44	75	80	65
4	81.58	81.58	84.21	94.44	94.44	94.44	70	70	75
5	78.95	81.58	76.32	94.44	100.00	94.44	65	65	60

Table 2 presents the results obtained in the previous work [16]. In that paper, different DWTs have been tested. The best accuracy was 86.84% achieved at level 2 and the 3rd scale of some wavelets: Daubechies, Symlet, Bior Splines, and Reverse Bior.

An accuracy of 80% was reached by Achraf et al. [14]. In their study, the authors have followed the process illustrated in Fig. 1(a), which is the extraction of MFCC coefficients from the speech signal and then classifying it using the SVM classifier.

The difference between the accuracy obtained in [14] (the one without transforming the signal by DWT) and the process (b) applied in the paper [16] is 8.55%. Meanwhile, the fact of using the DWT rather than the filter bank inside the MFCC extraction bloc (present work depicted in Fig. 1(c)) improves the accuracy of the detection system used in [14] by 2.18%. Thence we can conclude the importance of using the DWT in the part of signal processing of the prediction system.

Coming to the comparison between the process (b) proposed in the paper [16] and the process (c) suggested in this paper, it is noticed that the DWT was more effective when it was used in the speech signal transformation than when it was within the MFCC extraction bloc. At the same time, process (b) gives an accuracy improved by 6.23% than the one obtained by process (c).

Comparing both of the results reached by the use of the DWT before the MFCC extraction bloc [16] and the ones by the DWT within this bloc (present work), it is noticed that in the two methods, the best accuracy was shown with db2 at the 2 scales and with db3 at the 3rd scale respectively. The results reveal that using DWT outside the MFCC bloc gives a more accurate system.

5. Conclusion

This paper presents an approach to Parkinson's disease diagnosis centered on the MFCC and discrete wavelet transform. Daubechies wavelet has been used to filter signal after applying FFT by the third-scale approximation instead of using the triangular filter banks. Then extraction of the 12 cepstral coefficients. These coefficients have been applied in the classification using the SVM classifier, with the learning bases accounting for 73% of the database; the best accuracy was obtained at level 3 on the third scale.

The outcome of this paper is that the method consisting of DWT placed outside the MFCC bloc is more effective than this method where the DWT has been placed inside the bloc of MFCC. Therefore, it leads to conclude that the convenient and more accurate method to adapt is the one with the DWT before the MFCC bloc (to transform the speech signal) to fulfill the aim of building a crucial prediction system of Parkinson's disease.

References

[1] James Parkinson, "Anonymous an Essay on the Shaking Palsy," *London Medical and Physical Journal*, Vol.38, 1817.

[2] H. Karimi-Rouzbahani, M. Daliri, "Diagnosis of Parkinson's Disease in Human Using Voice Signals," *Basic and Clinical Neuroscience*, Vol.2, No.3, Pp.12 , 2011.

[3] Y. Campos-Roca, D. Monta, C.J. Perez. "Parkinson's Disease Detection Based on a Heterogeneous Acoustic Database," *Proceedings of the World Congress on Electrical Engineering and Computer Systems and Science* (EECSS 2015) Barcelona, Spain, Pp.13-14, 2015.

[4] A. Benba, A. Jilbab, A. Hammouch. "Discriminating Between Patients with Parkinson's and Neurological Diseases Using Cepstral Analysis," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Vol.24, No.10, Pp. 1100–1108, 2016.

[5] E. Benmalek, J. Elmhamdi, A. Jilbab. "Voice Assessments for Detecting Patients with Parkinson's Diseases in Different Stages," *International Journal of Electrical and Computer Engineering* , Vol. 8, No. 6, Pp. 4265-4271, 2018. ISSN: 2088-8708.
Doi: 10.11591/Ijece.V8i6.Pp4265-4271.

[6] B. Nsiri, S. Zayrit, T. Belhoussine Drissi, A. Ammoumou, "Features Selection By Genetic Algorithm Optimization with K-Nearest Neighbour and Learning Ensemble to Predict Parkinson Disease," *International Journal of Electrical and Computer Engineering (IJECE*) Vol. 12, No. 2, Pp. 1982-1989, 2022. DOI: 10.11591/Ijece.V12i2.Pp1982-1989.

[7] S. Savitha, A.N. Upadhya, J.H. Cheeranb. Nirmalc. "Thomson Multitaper MFCC and PLP Voice Features for Early Detection of Parkinson Disease," *Biomedical Signal Processing and Control*, Vol.46, Pp.293-30, 2018.

[8] Mrs.Snehal S. Golait, Dr.L.G. Malik, Prof.A.Thomas. "Handwritten Marathi Compound Character Recognition Using Structural and Statistical Features,"Impact Factor Value 3.441 E-ISSN: 2456-3463 *International Journal of Innovations in Engineering and Science*, Vol. 2, No.12, 2017. Www.Ijies.Net 13.

[9] N. Boualoulou, T. Belhoussine Drissi, B. Nsiri. "an Intelligent Approach Based on the Combination of the Discrete Wavelet Transform, Delta Delta MFCC for Parkinson's Disease Diagnosis," (IJACSA) *International Journal of Advanced Computer Science and Applications*, Vol. 13, No. 4, 2022.

[10] Sonali Lohbare (Pakhmode) and Swati Dixit. "Elimination of Noise From Ambulatory ECG Signal Using DWT," *International Journal of Engineering Trends and Technology,* Vol. 70, No. 5, Pp. 266-273, 2022. Crossref, Https://Doi.Org/10.14445/22315381/IJETT-V70I5P229.

[11] Raaed Faleh Hassan Et Al. "ECG Signal De-Noising and Feature Extraction Using Discrete Wavelet Transform," *International Journal of Engineering Trends and Technology* (IJETT), Vol.63, No.1, 2018.

[12] B. Magnin, L. Mesrob, S. Kinkingnéhun, M. Pélégrini-Issac, M. O. Colliot, M. Sarazin, H. Benali. "Support Vector Machine-Based Classification of Alzheimer's Disease From Whole-Brain Anatomical MRI," *Neuroradiology,* Vol.51, No.2, Pp .73–83, 2009.

[13] L. Jin, Y. Feng, J. He, S. Zhou, Q. Zeng & Y. Wu. "A Relieff-SVM-Based Method for Marking Dopamine-Based Disease Characteristics: A Study on SWEDD and Parkinson's Disease," *Behavioural Brain Research*, Vol.356, Pp.400-407, 2009.

[14] A. Benba, A. Jilbab, A. Hammouch, S. Sandabad. "Voiceprints Analysis Using MFCC and SVM for Detecting Patients with Parkinson's Disease," *1st International Conference on Electrical and Information Technologies ICEIT'2015*, Marrakech, Morocco, Pp. 300-304, 2015.

[15] A. Benba, A. Jilbab, A. Hammouch, "Voiceprint Analysis Using Perceptual Linear Prediction and Support Vector Machines for Detecting Persons with Parkinson's Disease," *the 3rd International Conference on Health Science and Biomedical Systems (HSBS '14),* Florence, Italy, Pp.22-24, 2014.

[16] T. Belhoussine, S. Zayrit, B. Nsiri, A. Ammoummou. "Diagnosis of Parkinson's Disease Based on Wavelet Transform and Mel Frequency Cepstral Coefficients," *International Journal of Advanced Computer Science and Applications,* Vol.10, No.3, 2019.

[17] Y. Toulni, T. Belhoussine Drissi, B. Nsiri. "Electrocardiogram Signals Classification Using Discrete Wavelet Transform and Support Vector Machine Classifier," *IAES International Journal of Artificial Intelligence* (IJ-AI) , Vol.10, No.4, Pp.960-970, 2021.DOI: 10.11591/Ijai.V10.I4.

[18] Z. Soumaya, B. D. Taoufiq, B. Nsiri, and A. Abdelkrim, " Diagnosis of Parkinson Disease Using the Wavelet Transform and MFCC and SVM Classifier," *IEEE 2019 4th World Conference on Complex Systems (WCCS)*, Ouarzazate, Moroccopp, Pp.1-6, 2019. Doi:10.1109/Icocs.2019.8930802.

[19] S. Zayrit, T. Belhoussine Drissi, A. Ammoumou and B. Nsiri, "Daubechies Wavelet Cepstral Coefficients for Parkinson's Disease Detection," *Complex Systems*, Vol.29, No.3, Pp.729–739,2020. Https://Doi.Org/10.25088/Complexsystems.29.3.729.

[20] Z. Soumaya, B. Drissi Taoufiq, N. Benayad, K. Yunus, A. Abdelkrim, "the Detection of Parkinson Disease Using the Genetic Algorithm and SVM Classifier," *Applied Acoustics*, Vol.171, Pp.107528, 2021. Doi:10.1016/J.Apacoust.2020.107528.

[21] M. Hoq, M.N. Uddin, S.-B. Park. "Vocal Feature Extraction-Based Artificial Intelligent Model for Parkinson's Disease Detection," *Diagnostics (Basel)*, Vol.11, No.6,Pp.1076, 2021. Https://Doi.Org/10.3390/ Diagnostics11061076.

[22] G. Solana-Lavalle, R. Rosas-Romero. "Analysis of Voice As an Assisting Tool for Detection of Parkinson's Disease and Its Subsequent Clinical Interpretation," *Biomedical Signal Processing and Control*, Vol.66, Pp.102415. Doi:10.1016/J.Bspc.2021.102415. 2021.

[23] Singh, Sanjana, and Wenyao Xu. "Robust Detection of Parkinson's Disease Using Harvested Smartphone Voice Data: A Telemedicine Approach," *Telemedicine Journal and E-Health: the Official Journal of the American Telemedicine Association*, Vol. 26, No.3, Pp.327-33, 2020. Doi:10.1089/Tmj.2018.0271.

[24] S. Aich, M. Joo, H. C. Kim, J. Park. "Improvisation of Classification Performance Based on Feature Optimization for Differentiation of Parkinson's Disease From Other Neurological Diseases Using Gait Characteristics," *International Journal of Electrical and Computer Engineering (IJECE*), Vol. 9, No. 6, Pp. 5176-5184, 2019. DOI: 10.11591/Ijece.V9i6.Pp5176-5184

[25] B.E. Sakar, M.E. Isenkul, C.O. Sakar, A. Sertbas, F. Gurgen, S. Delil, … O. Kursun. "Collection and Analysis of A Parkinson Speech Dataset with Multiple Types of Sound Recordings," *IEEE Journal of Biomedical and Health Informatics*, Vol.17, No.4, Pp.828–834,2013.

[26] Anett Antony Et Al. "Speaker Identification Based on Combination of MFCC and UMRT Based Features" *Procedia Computer Science*, Vol.143, Pp.250–257,2018.

[27] Wojcicki, K.: Writehtk. in: Voicebox Toolbox, 2011.Http://Www.Mathworks.Com/Matlabcentral/Fileexchange/32849-Htk-Mfcc-Matlab/Content/Mfcc/Writehtk.M.