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ISSN:2147-8228 http://dergipark.org.tr/ijamec **Original Research Paper**

Classification of Psychogenic and Laryngeal Voice Diseases Based on Wavelet Transform Analysis and Teager Energy Operator

Imen Hammami[1], Lotfi Salhi[1], Salam labidi[1]

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Abstract: Among several ways of communications, the voice remains the prominent tool for human. Therefore, the research in automatic voice pathology detection and classification area has gained much interest in the recent years. Indeed, these automatic systems may be used as assistive tools for the physicians during the clinical evaluation, to make decision whether the input voice signal belong to a healthy or unhealthy subject and to identify the nature of pathology. In this context, the paper provides a voice pathology detection and classification system based on wavelet analysis and Teager Energy Operator (TEO). In the first step, we used the voice signal that we taken form Saarbrücken Voice Database (SVD), to extract a set of features. In the second step, these feature vectors were used to feed a Gaussian Mixture Model (GMM) classifier for the sake of classification. The obtained results are 96.66% for the detection task and 92.5 % for the identification task using TEO. The combination of the three extracted features was tested and the reached accuracies were 92.22% and 86.11% for the detection and identification tasks, respectively. These results show that our proposal outperforms some state-of-art methods developed in the field of voice pathology identification.

Keywords: *Pathological Voices identification, SVD database, Wavelet Analysis, Teager Energy Operator, GMM*

1. Introduction

The identification and classification researches in the field of pathological voice are disregarded over the years. However, pathological voice detection (VPD) systems were widely developed in the literature. The numbers of people affected by vocal pathologies increases yearly, approximately 7.5 million people in the United States have trouble using their voices [2]. This large number may be due to the bad habits and people's jobs. The pathologies which affect the vocal folds during the phonation process; make it produced irregular vibrations due to the malfunctioning of different systems contributing to voice production [3]. Indeed, to produce the voice three main systems are involved: the respiratory system, the laryngeal system and the supra-laryngeal system (Fig.1). The nervous system has the prominent role in the control of the phonation process [4]. If one of these systems was affected the voice will be affected automatically. The voice impairments were derived from different origins: neurological, functional, laryngeal and psychogenic. For the speech production (expressive and receptive language), voice, resonance, articulation, fluency, and prosodic features are the major elements. When any one of these elements changes even moderately, our ability to communicate can be compromised [5].
As an alternative, to avoid the available apparatus using to assess patient's voice, digital processing of speech signals has provided a non invasive analytical technique which is considered to be an effective assisting tool to physicians when identifying voice impairments, specifically in their early stages. *Orozco-Arroyave et al.* [6], based on four methods were turned the voice signals into a set of relevant features (e.g. noise content measures, spectral-cepstral modelling, nonlinear features and measurements to quantify the stability of the fundamental frequency). Using these approaches they tried to discriminate between laryngeal, functional and neurological diseases. The obtained results show that for a particular disorder there are appropriate features to model it. Several studies have been developed in the literature; aiming to identify people with Parkinson diseases (PD) from others neurological or other kinds of diseases based on cepstral analysis and acoustic features reported a high accuracy rate near or up to 90% [7]– [12].

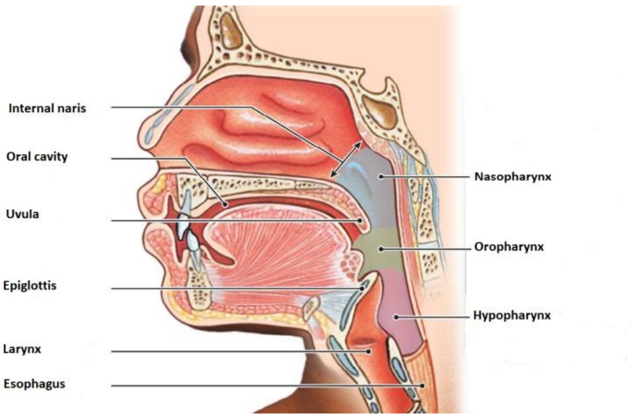

Fig. 1 The laryngeal system and the supra-laryngeal system

[1]*University of Tunis El Manar, Higher Institute of Medical Technologies, Department of Biophysics, Research Laboratory in Biophysics and Medical Technologies.*
[1] *ORCID ID: 0000-0002-6405-939X*
** Corresponding Author: Email: imenhammemi99@gmail.com*

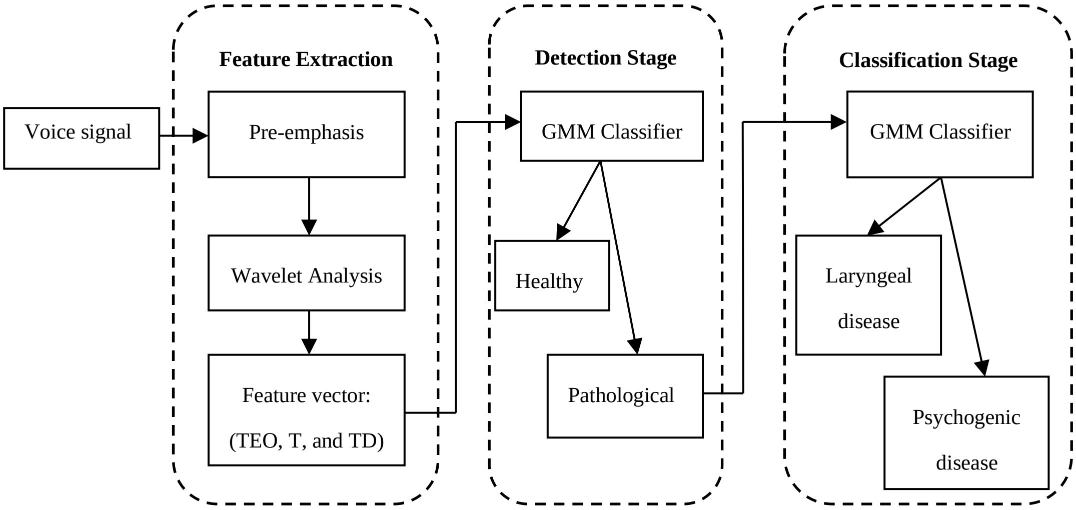

Fig. 2 The block diagram of the proposed system

Hugo Cordeiro et al. [13] based on short-term features (e.g. MFCC and LSF) developed a hierarchical classification system which combine three classifiers: support vector machines (SVM), Gaussian mixture models (GMM) and discriminant analysis (DA) to identify three classes: healthy, neuromuscular larynx pathologies (e.g. unilateral vocal fold paralysis) and physiological larynx pathologies (e.g. vocal fold edemas or nodules). The highest accuracy reported was 84.4%.
In this way, we try to invest in the field of pathological voice identification by developing a new pattern based on wavelet analysis and Teager Energy Operator (TEO) and other features to discriminate between psychological and laryngeal impairments.
This work is organised as follows: Section 2 devoted to describe the material used in this work and the developed methodologies: features extracted and the classifier. Section 3 presents the obtained results and the discussion and Section 4 contain a conclusion of all the work featured in this paper.

2. PROPOSED METHOD

The proposed method contains tree main steps: the first one is the feature extraction, the second one is the detection stage and the third one is the identification stage as shows in Fig.2. All the method steps were detailed in next subsection.

2.1. SVD corpus

Saarbrücken Voice Database (SVD) [1] is a free database elaborated by the Institute of Phonetics of Saarland University. This latter, contains recordings of sustained vowels, /a/, /i/ and /u/ for normal, high and low pitch. The recordings files were taken from healthy and pathological subjects who suffer from several kinds of disorders (e.g. dysphonia, cyst, laryngitis, etc). Furthermore, it contains a spoken sentence in German language: “Guten Morgen, wiegeht es Ihnen?” which means in English: “Good morning, how are you?”.

Table I. Distribution of SVD subset selected

	Normal	Laryngitis	Psychogenic dysphonia
Male	150	70	10
Female	100	50	70

Table I shows the subset selected from SVD database to perform our experience. From the whole database we choose a group of healthy subjects and two others groups of pathological subjects (which suffer from psychogenic dysphonia and laryngitis). The age of the chosen subject’s files recordings ranges between 25-70 years.

2.2. Wavelet transform

The wavelet transform analysis provides the so called time-frequency localization and multi-scale resolution, by suitably focussing and zooming around the neighborhood of one's choice. Unlike the Fourier transform, wavelets analysis can have infinite varieties which are fundamentally different from each other [14]. The wavelet domain contains more complicated basis functions called: the scaling function or father wavelet Φ (t) and the wavelet function or mother wavelet Ψ (t). A wavelet function is defined as [15]:

$$\Psi_{u,s}(t) = \frac{1}{\sqrt{s}}\,\Psi\left(\frac{t-u}{s}\right)(u \in IR, s \in IR_+^*) \quad (1)$$

Where ***s*** is the scale and ***u*** is the spatial displacement.

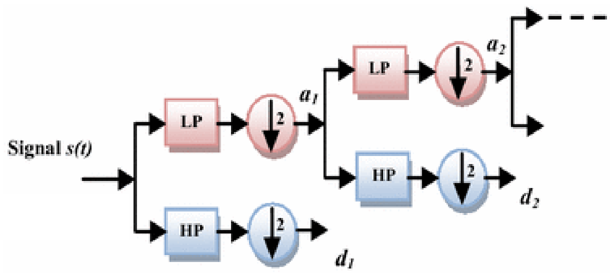

Fig. 3 Wavelet decomposition tree (Filter banks): three-level analysis

The wavelets which have strictly finite extent in the time domain are called discrete wavelets [14]. This latter, is based on sub-band coding using high-pass and low-pass filters. The discrete wavelet transform (DWT) is found to yield a fast computation due to his easy implementation which reduces the computation time and required resources.
Our proposal deals with feature extraction techniques based on discrete wavelet transform (DWT). Using wavelet analysis, the voice signal was turned into a series of wavelet coefficients, by applying successive low-pass filters which gives the approximation coefficients A[n] (low frequency information) and high-pass filters which gives the detail coefficients D[n] (high

frequency information). The discrete time-domain signal decomposition or Mallat-tree decomposition is shown in Fig.3. Indeed, the main selection criteria to choose a suitable mother wavelet is to have a wavelet function with enough number of vanishing moments in order to represent the salient features of the disturbance, as far as this wavelet should provide sharp cut-off frequencies [16]. The mother wavelet used in our proposed method is the Daubechies 40 (db40), which is an orthonormal wavelet. As described in [16], the number of vanishing moments of db40 wavelet is large, and hence it gives a meaningful wavelet spectrum of the analyzed signal (Fig.4). The decomposition was stopped to level 3 to decrease the complexity of the developed system.

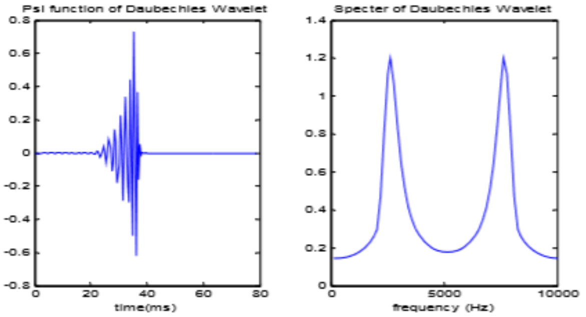

Fig. 4 Daubechies-40 wavelet: moment and spectrum

After the decomposition of voice signal using db40 at level-three, we extracted a set of robust features allowing the detection and identification of voice pathologies.

2.3. Features Extraction

Form the four wavelet coefficients, a set of three nonlinear parameters were extracted to create the feature vectors which describe properly the voice signal: the Teager Energy Operator (TEO), the Entropy (T), and the Theoretical Dimension (TD).

2.3.1. Teager Energy Operator (TEO):

The Teager Energy Operator (TEO) [17], [18] is defined as the nonlinear energy. Based on this feature we can estimate the envelope amplitude and the instantaneous frequency of a speech signal [19] and the energy changes of signals composed of a single time-varying frequency [20]. The Teager Energy Operator is defined in the continuous case as [21]:

$$\Psi\big(x(t)\big) = \dot{x}^2(t) - x(t)\ddot{x}(t) \qquad (2)$$

Where x(t) is the signal, $\dot{x}$ is the first derivative of x and $\ddot{x}$ is the second derivative. In the discrete case TEO is expressed as follows:

$$\Psi\big[x[n]\big] = x^2[n] - x[n-1]x[n+1] \qquad (3)$$

The Teager Energy Operator was used in several areas like signal processing [22], [23] and image processing (e.g. contrast enhancement).

2.3.2. Entropy (T):

The Entropy (T) criterion measures the uncertainty of a random variable more precisely in the area of signal processing, it describes information related properties for an accurate representation of a given signal [16]. The most common definition is the Shannon's entropy, which is expressed as:

$$T(x) = -\sum_i x_i^2 \log x_i^2 \qquad (4)$$

Where $\boldsymbol{x_i}$ stands to the wavelet coefficients at level $\boldsymbol{i}$.

2.3.3. Theoretical Dimension (TD):

The Theoretical Dimension (TD) is a measure of the energy concentration of the signal decomposition based on orthogonal wavelet mother [24]. It is a criterion which reflects the degree of organization of information in the speech signal. It is defined as [25]:

$$TD = \frac{1}{N}e^H \qquad (5)$$

Where $\boldsymbol{N}$ is the size of the signal $\boldsymbol{x_i}$ and $\boldsymbol{H}$ is the mean wavelet entropy:

$$H = \frac{1}{N}\sum_i x_i^2 log(x_i^2) \qquad (6)$$

2.4. Gaussian Mixture Model (GMM)

The Gaussian Mixture Model (GMM) [26] is one of the most important modelling methods used to resolve the problems of classification in different areas like speaker recognition, pathological voice detection and identification and image processing. The GMM copes more with the space of the features rather than the time sequence of their appearance [27]. The main idea of the GMM is to generate a mixture of Gaussian densities to model a set of a given data. The model density is a weighted sum of *M* component densities expressed as:

$$P(X) = \sum_{k=1}^{M} \alpha_k g(X|\mu_k, C_K), k = 1,2, \dots, M \qquad (7)$$

Where α_k, μ_k and C_k are the weight, the mean vector and the covariance matrix of the *i*-th Gaussian component, respectively.

3. Experimental setup

For pathological voice detection and classification we proposed a new system based on nonlinear features extracted from wavelet coefficients and GMM classifier. From the SVD database we selected a subset of sustained vowel /a/ recordings of three classes: healthy subjects, subjects who suffer from laryngitis (laryngeal class) and subjects suffer from psychogenic dysphonia (psychogenic class). The voice signals were decomposed using Daubechies wavelet (db40) at level three. As a consequence we obtained three detail coefficients and one approximation coefficient. From each wavelet coefficients three features were extracted which are: the Teager Energy Operator (TEO), the Entropy (T) and the Theoretical Dimension (TD) as shown in Table II. The combination of the three feature vectors result a new feature vectors which contains 12 features, was tested in the detection and identification stages.

Each detection and classification stages were performed using three GMM models. For the pathological voice detection we used GMMs with 8, 32, and 64 Gaussian mixtures (Fig. 5), and in the pathological voice identification 8, 16, 24 Gaussian mixtures were used (Fig. 6). The database was divided equally into five-fold, where each time one set is used as a test set whilst the remaining sets performed the training step. Consequently, all the data were used in the test step.

Table 2. Input vectors for GMM classifier

Vectors	Feature vector
V1	Teager Energy Operator (TEO)
V2	Entropy (T)
V3	Theoretical Dimension (TD)
V4	(TEO, T and TD)

4. Metrics

The performances of the conducted experiments were expressed in terms of sensitivity (S_n), specificity (S_p) and accuracy (A_{cc}). These letters are defined as follow:

$$S_n = \frac{TP}{TP + FN} * 100 \quad (8)$$

$$S_p = \frac{TN}{TN + FP} * 100 \quad (9)$$

$$A_{cc} = \frac{TP + TN}{TP + TN + FP + FN} * 100 \quad (10)$$

Where (TP) is the true positive: when the system detects a pathological subject as a pathological subject, (TN) is the true negative: when the system detects a normal subject as a normal subject, (FP) is the false positive: when the system detects the normal subject as pathological subject and (FN) is the false negative: when the system detects the pathological subject as normal subject.

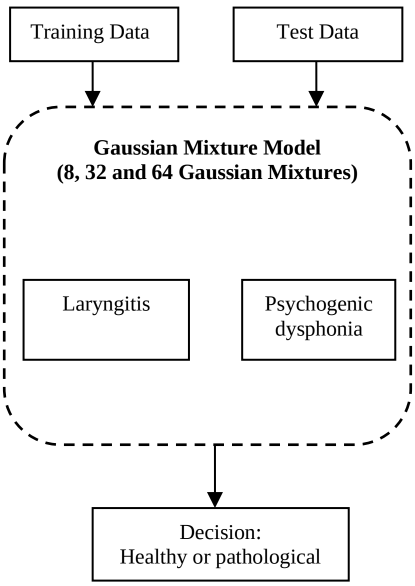

Fig. 5 Pathology voice detection

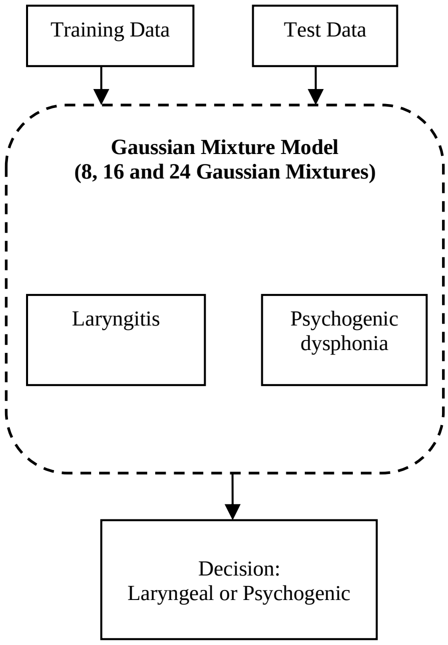

Fig. 6 Pathology voice identification

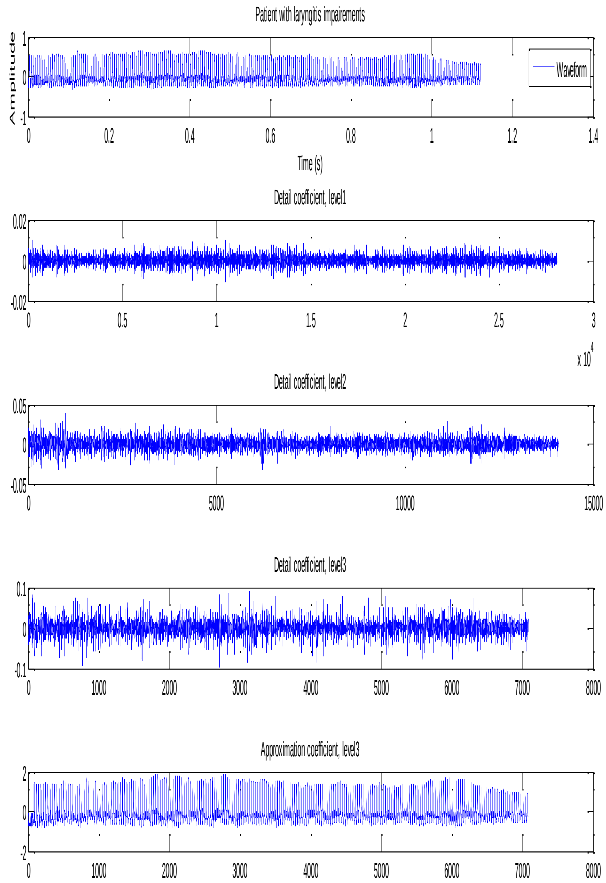

Fig. 7 Wavelet analysis of the sustained vowel /a/ signal of woman that suffer from Laryngitis impairments

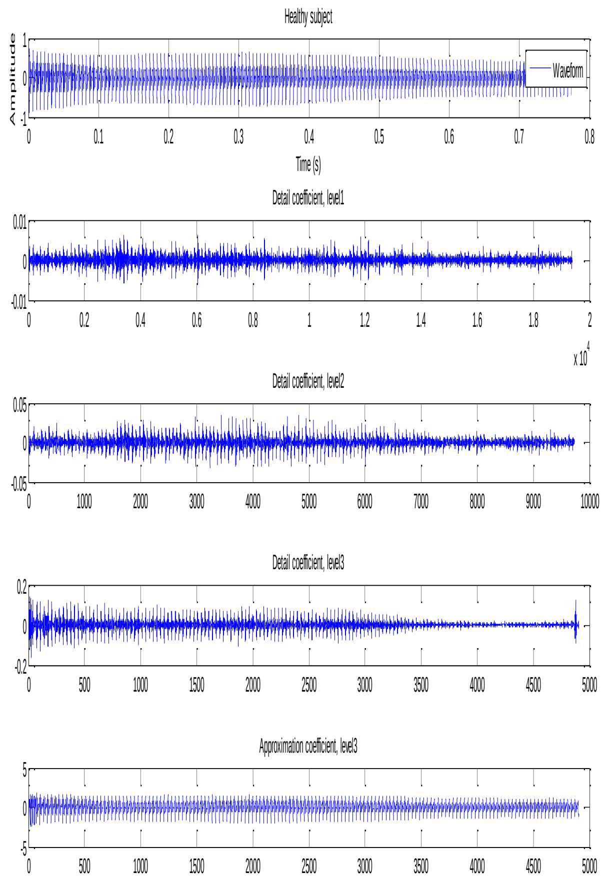

Fig. 8 Wavelet analysis of the sustained vowel /a/ signal of Healthy woman

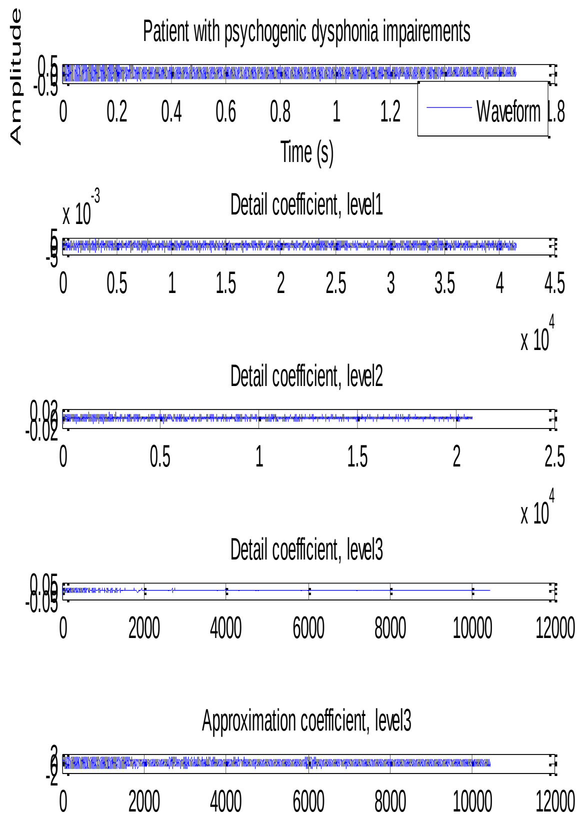

Fig. 9 Wavelet analysis of the sustained vowel /a/ signal of woman that suffer from Psychogenic Dysphonia

5. Results and discussion

In this work we developed a new system to discriminate between healthy and pathologic subjects as a first stage. Afterwards, the system will perform the identification process between two classes: laryngeal disease and psychogenic disease. Based on Discrete Wavelet Transform analysis, the proposed system decomposed the selected signals from SVD database via Daubechies 40 at level three. As a result, we have obtained four coefficients; Fig. 7, 8 and 9 depicted the wavelet decomposition for three different women voices (a healthy woman, a woman who suffer from laryngeal impairment and a woman that suffer from psychogenic impairment). From these coefficients a set of parameters such as Teager Energy Operator (TEO), Entropy (T) and Theoretical Dimension (TD) were extracted. In order, to classify the set of the extracted data, several Gaussian Mixture models were developed and tested. During the detection stage three GMM systems were setting with different number of Gaussian mixtures (8, 32 and 64) and the results were shown in Table III. The best accuracy achieved was 96.66% for using TEO and a GMM with 32 Gaussian Mixtures. Nevertheless, for a GMM classifier with 8 and 64 mixtures the accuracy rate decreases (87.77% for a GMM with 8 mixtures, and 95.55% for a GMM with 64 mixtures). The combination of the three feature vectors extracted from the four wavelet coefficients reported an accuracy rate equal to 92.22% using a GMM with 32 Gaussian Mixtures. The best accuracy achieved was for using TEO with 32 Gaussian Mixtures.

Table 3. Performance measures for pathology detection

Features	Gaussians	Sn (%)	Sp (%)	Acc (%)
TEO	8	90	85	87.77
	32	98	95	**96.66**
	64	98	92.5	95.55
T	8	88	80	84.44
	32	88	85	**86.66**
	64	86	80	83.33
TD	8	82	80	81.11
	32	86	82.5	**84.44**
	64	80	77.5	78.88
Combination (TEO, T, TD)	8	90	90	91.11
	32	94	90	**92.22**
	64	86	85	85.55

In the identification stage, we used three GMM systems to classify the extracted data into two classes' laryngeal disease and psychogenic disease. The best accuracy reached is 92.5% when we used the Teager Energy Operator (TEO) and a GMM classifier with 24 mixtures. However, using GMM with 8 and 16 mixtures do not give a good result. Likewise, the combination of three feature vectors in the identification stage did not report a good accuracy rate (86.11%) as show in Table IV.

The Entropy parameter was widely used in the field of pathological voice detection and it gives a good result [16], [28] combining with other classifier (e.g. support vector machine and neural network). However, in our work using the Entropy as input data for the GMM classifier gave accuracies rate equal to 86.66% and 87.5% for the detection and identification tasks, respectively. In addition, the Theoretical Dimension gave the lower accuracies values for both the detection and identification stages. The accuracies reached were 84.44% and 67.5% for the detection and identification tasks respectively. The best results obtained for the detection and identification tasks were shown in Fig.10 and Fig.11 with the results of features combination experiments. Fig.12 shows a comparison of our proposed method with other methods using the same voice database (SVD). *Al-Nasheri et al.* [29] used a subset of normal and pathological subjects (suffer from cyst, polyp and paralysis) to extract features from different frequency bands. These features were used to feed an SVM classifier and the obtained accuracy was 90.979%. However, the same authors in [30] extract a set of multi-dimensional voice program (MDVP) features from the same selected subset from SVD voice database. The proposed method reported an accuracy of 99.68%. This can be explained by used of the Fisher Discriminant Ratio (FDR) as a feature selection method combined with the SVM classifier to improve the correct rate value. In our study the obtained results were promising comparing with other methods and we can improve it using a feature selection method.

Table 4. Performance measures for pathology identification

Features	Gaussians	Sn (%)	Sp (%)	Acc(%)
TEO	8	62.5	62.5	62.5
	16	62.5	62.5	62.5
	24	93.75	91.66	**92.5**
T	8	56.25	54.16	55
	16	68.75	58.33	62.5
	24	87.5	87.5	**87.5**
TD	8	56.25	50	52.5
	16	56.25	50	52.5
	24	81.25	58.33	**67.5**
Combination (TEO, T, TD)	8	65	68.75	66.66
	16	75	81.25	77.77
	24	85	87.5	**86.11**

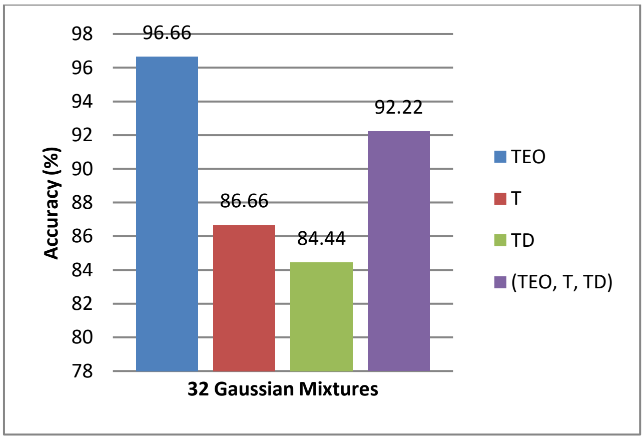

Fig.10 The best performance of the GMM classifier in detection Stage with 32 Gaussian Mixtures

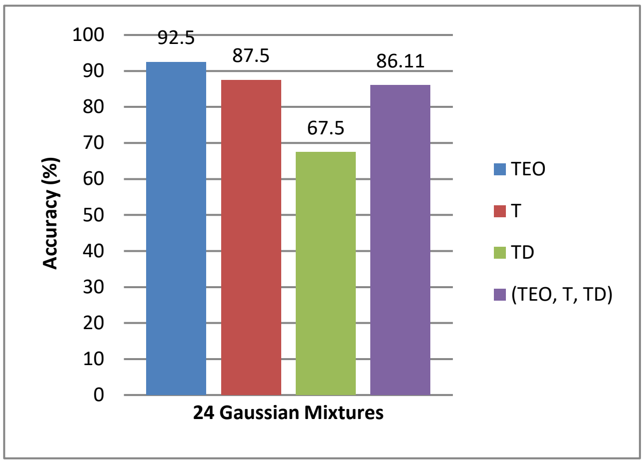

Fig. 11 The best performance of the GMM classifier in identification Stage with 24 Gaussian Mixtures

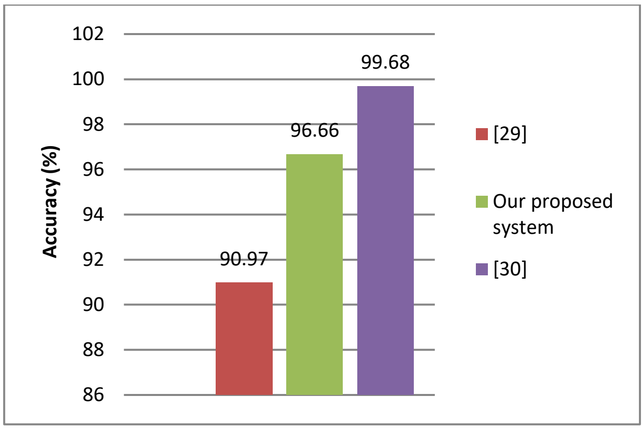

Fig .12 Comparison of the performance of our proposed method with other methods using the SVD database

6. Conclusion

In this work we had tried to discriminate between three voice classes in two stages. The first stage is devoted to discriminate between pathological and healthy subjects. Whilst, the second stage is devoted to discriminate between two voice impairments (laryngeal disease and psychogenic disease). Indeed, to perform our proposed method we extracted a set of feature from wavelet coefficients. A GMM classifier combined with Teager Energy Operator (TEO) gave prominent results. The accuracies rate reported were 96.66% and 92.5% for the detection and the identification tasks, respectively. The results of the features combination were mediocre. As a future works we are going to discriminate between several classes of voice pathologies based on a new approach.

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