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The Separation of Multi-Class Pathological Speech Signals Related to Vocal Cords Disorders Using Adaptation Wavelet Transform Based on Lifting Scheme

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Abstract. Achievement to a non-invasive method to properly diagnose the diseases is a significant subject in domain of speech processing. The aim of this paper is to apply non-invasive methods to do diagnosis, provide preventive strategies and plan for treatment aids and treatment. Regarding the speech disorders based on wavelet features of common wavelet although have relatively proper performance, it is expected that design optimizations based on the features of speech signal and classifier performance lead to improvement of results. To design the adaptive wavelet transform, the parameters of lifting scheme generating bi-orthogonal wavelet are initially applied and then they are optimized through genetic algorithm and classification performance of Support Vector Machine. The result separation of normal and pathological signals provides an accuracy of 100 percent. Also, the result of two-class and three-class separation of six disorders using adaptation wavelet based on lifting scheme which indicative the advantage of suggested method with other mother wavelet.

Keywords: Lifting Scheme; Speech Signal Processing, Vocal Cords Disorders, Support Vector Machine, Genetic Algorithm.

1. INTRODUCTION

The early diagnosis of different types of diseases and disorders of human speech production system through non-invasive methods and using diverse techniques of processing speech signals are subjects which have pay attention to researchers of medical sciences and signal processing. In fact, the presumed objectives in such domains are developing new techniques and enhancing ability the existing methods and algorithm of processing through which the registration of speech signals outside of the body could be done with high degree of precision. Then, these signals can be used for some diagnostic measures and they might provide treatment aids and treatment strategies. There are different methods for diagnosis of larynx diseases each of which examine a section of patient's larynx and they have different costs, accuracies and levels of confidence. Of these methods, one could point to simple examination of larynx, lymph glands and the neck by physician, X-ray tomography of the larynx, larynx radiography by Fluoroscope to examine the shape and structure of larynx, plain chest imaging methods such as computerized tomography scan, radiography through magnetic resonance imaging (MRI) scan, biopsy to do microscopic analysis of the intended tissue and examination of the inner surface of the larynx through a system called "Laryngoscopy". In general, the advantage of using signal registration methods in noninvasive method is that compared with invasive methods in which expensive and complicated devices and high cost and duration are needed for imagining the interior of the body (e.g. Videostroboscopy of changes in the vocal cords in the larynx), signal registration methods do not need costly devices to register signals outside of the body. These methods are quick, convenient and iterative methods for diagnosis of clinical pathology in speech production system of human. Therefore, the significance of examination and applied methods in the present project is that through them, it is possible to register a portion of voiced speech signal of patients by the simplest and the least costly devices (e.g. A microphone) without spending a large time and cost or risks of anesthesia and surgery. These methods significantly contribute to

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determination of the changes in the natural functions of vocal cords due to presence of pathological factors and analysis of their representation on speech signal. Therefore, the existing processing methods enable us to determine the possibility of such disorders and diseases in the initial stages of their formation with an acceptable level of confidence, and in the next stage, it is possible to define the type of disease and provide the necessary conditions for their proper treatment.

In papers associated with diagnosis of larynx diseases, different methods have been applied. For instance in [1], features based on non-linear analysis of time series such as largest lyapunov exponent, fractal-scaling analysis, estimations of the entropy, noise parameters and cepstrum coefficients were extracted and different classifiers such as Hidden Markov Models (HMM), Gaussian Mixture Model (GMM) and Support Vector Machines (SVM) were used. The best separation result was 98.23 percent. In [2], the frequency and bandwidth of the first peak of packet-spectral LPC were used for selection of feature and SVM classifier was also utilized which led to 100 percent accuracy of separation results. In [3], Mel Frequency Cepstral Coefficients (MFCC) and energy coefficient as well as a combination of MFCC, jitter and shimmer Coefficients were used for extraction of features. These coefficients combined with Gaussian Mixture Model (GMM) and Support Vector Machines (SVM) presented an accuracy of 82.6 percent. In [4], wavelet packets with double filter-banks were used to extract energy and entropy features. To separate Edema, Nodule and Polyps, SVM and genetic algorithm were used which led to an accuracy of 94.12 percent. In [5], the linear-characteristics wavelet was extracted and Local Discriminant Bases (LDB) and Genetic Algorithm (GA) were used to separate vocal fold polyp from spasmodic dysphonia, and vocal nodules and keratosis leukoplakia. The separation percentage of vocal fold polyp from spasmodic dysphonia disorders was 82.5 percent. For keratosis leukoplakia, it was 81.81 percent and for vocal nodules, it was 87.50 percent. In [6], wavelet transform and artificial neural network (ANN) were suggested for separating pathological normal voice signals from normal ones. The results show that the suggested method of wavelet transform is a proper method for separation of normal and pathological signals which generated an accuracy of 93.33 percent in the best case. In [7], discrete wavelet packet, multi-class linear discriminant analysis and multi-layer artificial neural network were used to develop a classification system for recognition of patient's voice. The extracted features for normal and pathological voices were determined through Shannon energy and entropy methods. The obtained results made it possible to separate normal and pathological cases with respective an accuracy of 96.67 and 97.33 percent for Shannon energy method and Shannon entropy method, respectively.

In previous studies, diverse methods for tracking the remaining effects on speech signals as a result of different disorders were discussed by active scholars on voice disorders the majority of which reviewed the separation pathological from normal voice signals. In other words, the diagnosis of exist of disorders, not their type, is emphasized because separation of different types of diseases is less emphasized by scholars due to distinctive complications. Therefore, the present study endeavors to diagnose vocal cord disorders and perform multi-class separation of different types of diseases.

This paper is organized as follows: Section 2 describes the database. In Section 3, the extraction of feature based on suggested method of wavelet transform by lifting scheme is discussed. Section 4 describes the applied classifications and results of normal and pathological separation. Discussion is presented in Section 5 and Section 6 provides the conclusions.

2. DATABASE

Due to the fact that diagnosis and development of treatment methods of larynx disorders, especially vocal cords are accompanied by analysis of changes in nature vibration of vocal cords, the tests and analyses of present study pay attention to vowel sounds compared to voiceless ones. Therefore, the implementation of diagnostic methods of larynx diseases is done through selection of a database which uses voiced sounds. In the present study, the voice samples examined were selected from Disordered Voice Database [8], model 4337, version 1.03 (Kay Elemetrics Corporation, Lincoln Park, NJ), This database was developed from Massachusette Eye and Ear Infirmary (MEEI) Voice and Speech Lab and it included 57 normal and 653 pathological signals. In each signal, the individual pronounced vowel /a/ for few seconds. To reduce the disruptive effects of destructive noise on recording of signals, voice recordings were made in a special soundproof in which the sampling frequency was 44.1 kHz in mono-channel. One of the reasons of selecting this database was its repetitive application in other papers and studies. This enables different authors to compares their methods as applied on an identical database. The disorders included in the present project were: Paralysis, paresis, Vocal nodules, vocal fold edema, vocal fold polyp, keratosis leukoplakia.

3. FEATURE EXTRACTION METHOD

Since the objectives of present study are separation of normal and pathological speech signals and diagnosis of type of diseases, one can design the wavelet based on classifier performance. In this regard, the wavelet parameters were set in a way that its features can be separated in classification stage with a high accuracy. The implementation of such an algorithm necessitates the solution of two problems: The first is parameterization of wavelet to use it in optimization algorithm and the second is the design of parameter optimization system to obtain proper results in separation of signals. Each one of these problems can be solved through different approaches. In this paper, the method of wavelet parameterization through lifting was reviewed and its performance was evaluated through joint parameter search genetic algorithm system.

3.1. WAVELET DESIGN BY LIFTING SCHEME

Lifting is used for design of new wavelets and analysis of existing wavelets into their primary blocks [9]. This technique was developed to generate second-generation wavelets in non-Euclidean spaces. In such spaces, it is impossible to transfer, add and open the wavelet. These two measures form the fundamental bases of first-generation wavelets. In the present section, authors endeavor to apply lifting scheme for design of bi-orthogonal wavelets with support of finite-time support and optimal features. One of the advantages of these wavelets compared with orthogonal wavelets is that during implementation of bank filter there is no need for equality in the length of two filters. This can be regarded as representing a higher degree of flexibility for these types of wavelets. On generation of wavelet, lifting enables the calculation of wavelet transform coefficients in a more optimal method. This method increases the rate of calculations and in this regard, it is deemed as highly significant. Figure (1) shows the bank filter associated with bi-orthogonal wavelet transform. $\tilde{h}_O, \tilde{h}_I$ respectively refer to low-pass and high-pass filters. For synthesis, another filter pair, $h_O$and h_I, exist. As shown, there are two pairs of filters in bi-orthogonal systems for synthesis and analysis in contrast to orthogonal systems in which only one pair of filters are definable.

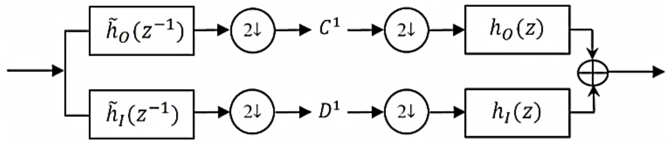

Figure 1. Wavelet Transform with Sub-band [9]

Both filter pairs of figure (1) are presumed to be FIR. It is possible to thoroughly reconstruct the signal after analysis if the following conditions are observed:

$$h_O(z)\tilde{h}_O(z^{-1}) + h_I(z)\tilde{h}_I(z^{-1}) = 2 \quad (1)$$

$$h_O(z)\tilde{h}_O(-z^{-1}) + h_I(z)\tilde{h}_I(-z^{-1}) = 0 \quad (2)$$

Laurent polynomials are defined with the equation (3):

$$h(z) = \sum_{k=k_b}^{k_e} h_k z^{-k} \quad (3)$$

In the above equation, coefficient h_k is non-zero for a finite number of k. If we consider k_e and k_b as respectively representing the least and highest possible value of k and $(k_e - k_b)$ is the degree of polynomials. Each filter of figure (1) represents a Laurent polynomial:

$$h_O(z) = h_{Oeven}(z^2) + z^{-1}h_{Oodd}(z^2) \quad (4)$$

In the equation (4), $h_{Oeven}$and h_{Oodd}respectively represent even and odd sections of $h_O$filter calculated from equations (5-8):

$$h_{Oeven}(z) = \sum_k h_{O2k} z^{-k} \quad (5)$$

$$h_{Oodd}(z) = \sum_k h_{O2k+1} z^{-k} \quad (6)$$

$$h_{Oeven}(z^2) = \frac{h(z) + h(-z)}{2} \quad (7)$$

$$h_{Oodd}(z^2) = \sum_k h_{O2k+1} z^{-k} \quad (8)$$

Bi-orthogonal filters can be represented through poly-phase matrix, but the analysis and synthesis of pair filters have their distinctive poly-phase matrix. This matrix for synthesis and analysis filters is represented in equations (9-10).

$$P(z) = \begin{bmatrix} h_{Oeven}(z) & h_{Ieven}(z) \\ h_{Oodd}(z) & h_{Iodd}(z) \end{bmatrix} \quad (9)$$

$$P(z) = \begin{bmatrix} \tilde{h}_{Oeven}(z) & \tilde{h}_{Ieven}(z) \\ \tilde{h}_{Oodd}(z) & \tilde{h}_{Iodd}(z) \end{bmatrix} \quad (10)$$

Using poly-phase representation, the wavelet transform in figure (1) can be represented as figure (2).

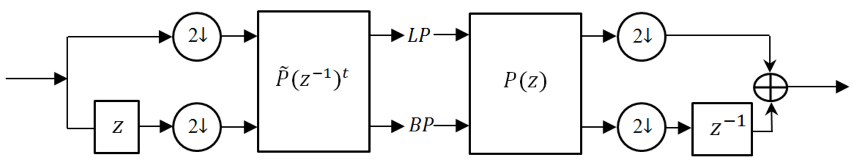

Figure 2. Representation of Wavelet Transform in P and $\tilde{P}$Matrix

Now, the perfect reconstruction condition can be rewritten as $P(z)\tilde{P}(z^{-1})^t = I$. Lifting is an association between h_O, h_I pair filters which has the perfect reconstruction condition and are common in low-pass and high-pass filters. In the following, the equations of lifting scheme are developed:

Lifting: Let's suppose that h_O, h_I filters are complementary. Each FIR filter is similar to h_I^{new} in acting as complement for h_O and it has the equation (11):

$$h_I^{new}(z) = h_I(z) + h_O(z)s(z^2) \tag{11}$$

In equation (11), $s(z^2)$ is a Laurent Polynomial. Each filter that has the form of equation (11) is a complement of h_O. The new poly-phase matrix obtained through replacement of h_I^{new} for h_I is:

$$P^{new}(z) = \begin{bmatrix} h_{Oeven}(z) & h_{Oeven}(z)s(z) + h_{Ieven}(z) \\ h_{Oodd}(z) & h_{Oodd}(z)s(z) + h_{Iodd}(z) \end{bmatrix} = P(z)\begin{bmatrix} 1 & s(z) \\ 0 & 1 \end{bmatrix} \tag{12}$$

It is evident that the determinant of new poly-phase matrix is always 1 which is support for the supposition that h_I^{new} is a complement of h_O. To apply of lifting on low-pass filters h_O and $\tilde{h}_O$ leads to the equations (13-14):

$$\tilde{h}_O^{new}(z) = \tilde{h}_O(z) - \tilde{h}_I(z)s(z^{-2}) \tag{13}$$

$$\tilde{P}^{new}(z) = \begin{bmatrix} \tilde{h}_{Oeven}(z) + \tilde{h}_{Ieven}(z)s(z) & \tilde{h}_{Oodd}(z) + \tilde{h}_{Iodd}(z)s(z) \\ \tilde{h}_{Ieven}(z) & \tilde{h}_{Iodd}(z) \end{bmatrix} = \begin{bmatrix} 1 & s(z) \\ 0 & 1 \end{bmatrix}\tilde{P}(z) \tag{14}$$

The lifting structure is schematically shown in figure (3). With addition of lifting steps to normal wavelets, one can enhance it. To do this, the selection of s(z) filter is done in a way that the resulting wavelet has the intended characteristics. Output feature of signal using a two-channel filter bank by lifting scheme, as depicted in figure (3), where C^1, D^1 are low-pass and high-pass filter coefficient respectively, indicates from one step wavelet decomposition. The algorithm proposed in this study, continuing the signal decomposition to 7-level. Feature extraction of the signal using a dual-channel filter banks by lifting scheme be done according to figure (3), that C^1 is low-pass coefficient and D^1 high-pass coefficient from one stage analysis shown. Suggested algorithm in this study, analysis of the signal to 7 level.

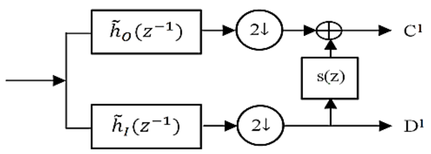

Figure 3. Lifting Structure

Coefficients are obtained: d^1 to d^7 and c^7. To generate efficient features for each of the above coefficient, the amount of energy according to equation (15) is calculated [10]:

$$E_{\|\,\|}: R^l \to R^d,\ (c^d, d^d, \ldots, d^1) \mapsto (\|d^d\|, \ldots, \|d^1\|) \tag{15}$$

Where l is the signal length and d is the number of successive levels. Figure (4) illustrates a brief schema of the suggested feature extraction phase.

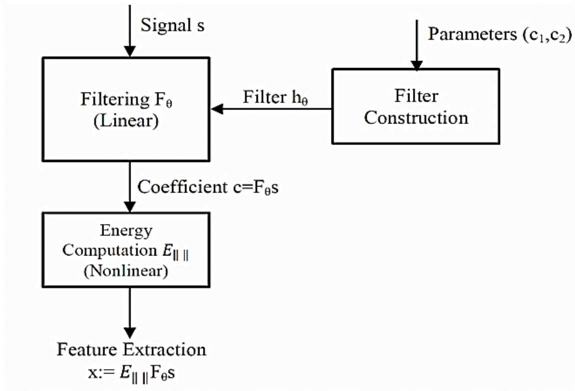

Figure 4. Feature Extraction Process [10]

In the next section, the authors intend to add a lifting stage to wavelet filters 2 so as to lift the s(z) of this wavelet in a way that its features can be separated with high accuracy.

4. CLASSIFICATION PROCEDURE OF EXTRACTED FEATURES

4.1. SUPPORT VECTOR MACHINE

The initial idea of this method was proposed by Vapnik in 1979. SVM based on structural risk minimization principle (SRM), which two main objectives will follow. The first is to control the empirical risk on the training data set. The second is to control the capacity of the decision functions used to obtain this risk value. Assume that the training data with *k* number of samples are represented by $\{x_i, y_i\}, i = 1, \dots, k,$ where $x \in R^n$ is an n-dimensional vector and $y \in \{-1, +1\}$ is the class label. The aim is to find a hyper-plane that divides the data so that all the points with the same label are on the same side of the hyper-plane. This depends on finding *w* and *b* such that [11-12]:

$$y_i(w.x_i + b) > 0 \tag{16}$$

If a hyper-plane exists that satisfies (16), the two classes are said to be linearly separable. SVM approach is such that by changing parameters of the hyper-plane, finds the hyper-plane with maximum Euclidian distance from the training set. According to the SRM principle, there will be just one optimal hyper-plane with a specific maximal margin, defined as the sum of distances from the hyper-plane to the closest points of each class. This linear classifier threshold is the optimal separating hyper-plane, referred to as OSH [4]. In case of linearly separable classes, it is possible to rescale *w* and *b* so that:

$$\min_{1 \le i \le k} y_i(w.x_i + b) \ge 1 \tag{17}$$

Therefore, (16) can be revised as below:

$$y_i(w.x_i + b) \ge 1 \tag{18}$$

Regarding (18), distance to the closest point is $1/\|w\|$ and the OSH can be found by minimizing $\|w\|^2$ under constraint (17). The minimization procedure uses Lagrange multipliers and quadratic programming (QP) optimization methods [4]. In the case of non-separable training sets, the i-th data point has a slack variable ξ_i, which represents the magnitude of the classification error. A penalty function *f(n)* represents the sum of these misclassification errors as:

$$f(\xi) = \sum_{i=1}^{l} \xi_i \tag{19}$$

In this case (18) can be written as follows:

$$y_i(w.x_i + b) + \xi_i \geq 1 \tag{20}$$

The SVM solution can be found by keeping the upper bound on the VC dimension small and by minimizing an upper bound on the empirical risk, for example the number of training errors with the following minimization, under constraint (20):

$$\min_{w,b,\xi_i} \left[\frac{1}{2} \|w\|^2 + C \sum_{i=1}^{k} \xi_i \right] \tag{21}$$

The first term in (21) is the same as in the linearly separable case to control the learning capacity, while the second term controls the number of misclassified points. The regularization constant C>0 determines the trade-off between the empirical error and the complexity term. Parameter C is chosen by the user and a large C corresponding to the assignment of a higher penalty to errors.

Figure (5) depicts how an SVM classifier works. An SVM is a binary classifier and could be efficiently employed in our primary task, which is distinguishing two classes of signals (pathological voices vs. normal ones).

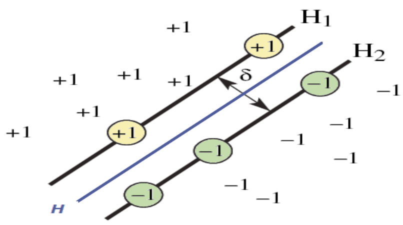

Figure 5. Formation of the Separation Hyper-Plane through Support Vectors.

After selection of features, the categorization of classes and training the classifier to diagnosis speech disorders should be done. The intended classification uses SVM classifier. The criterion for selection of advantageous properties is the classifier performance. Therefore, to scoring for each group of feature which the result of a set of wavelet parameters, one should measure the accuracy of separation of pathological from normal voice signals. In the following, the authors intend to add a lifting stage to daubechies2 (db2) wavelet filters in order to lift this wavelet in a way that its features can be separated with an accuracy of 100 percent. In this regard, s(z) filter is regarded in the following manner:

$$s(z) = c_1 + c_2 z^{-1} \tag{22}$$

Determination of c_1 and c_2 coefficients depends on problem's objective and it is done in different methods. In most of the published papers, the objective of wavelet design based on lifting is compression. Therefore, the above-mentioned coefficients are selected in a way that they minimize the entropy of coefficients [13]. But the present paper, aims to separation of pathological from normal voice signals. As the authors found out, the coefficients vector (c_1, c_2) contributed to classifier in attaining the highest possible accuracy in separation of normal and pathologic cases of KAY database.

4.2. GENETIC ALGORITHM

The main ideas behind genetic algorithm are the laws of nature. In an algorithm, individuals of higher competencies possess higher opportunities of marriage and reproduction. Therefore, more performance children are born after several generations. Genetic algorithms can be regarded as randomize optimization methods which gradually align towards the optimal point. Regarding the features of genetic algorithm in comparison with other optimization methods, one could say that genetic algorithm is an algorithm which can be applied for any type of issue and it has a verified advantage in attaining general efficiency. Genetic algorithm iteratively refines a set of answers so that in each stage, a set of individuals are selected as parents by which the next generation of children forms.

Genetic algorithm executes a one-sided random research to find a general optimization. The advantage of this method compared with gradient reduction method is that it does not get involved in local optimized points. On the other hand, this method is better than random algorithms because it can take the problem towards relatively effective areas in search space. The used operators in genetic algorithm include: Selection, intersection, Mutation and Substitution. The search procedure is led by a fitness function which measures the fitness of each generation [14]. In the present study, the criterion of fitness for the features was the result of SVM classifier. Therefore, if SVM accuracy is used as a criterion of fitness, the genetic algorithm search results in parameters through which the best features are generated. Figure (6) shows the suggested search algorithm of the best adaptive wavelet parameters.

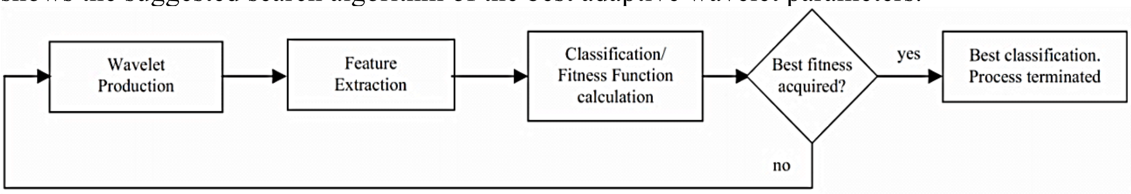

Figure 6. Search Algorithm of Best Wavelet Parameters

In this case, $s(z) = c_1 + c_2 z^{-1}$ vector is loaded with initial random values c_1 and c_2. To determine of filter coefficients, the analysis of signals proceeds up to level 7 using DWT. The energy of each final branch is calculated and for each signal, 8 features are generated. The obtained features belong to pathologic and normal classed (653 pathological and 57 normal individuals of KAY database) which were used in four stages and rotational manner to train and test SVM classifier with radial basis function (RBF) kernel. The four accuracies obtained were averaged the result of which was considered as the value of fitness function of initial vector s(z). Regarding fitness function, new values are defined for s(z) vector and the above operation continues until the highest accuracy is obtained. If the search algorithm attains this value of accuracy, the operation will stop and present parameter vector (c_1, c_2) is considered as the optimal vector [15]. The progress of genetic algorithm in solving the optimization problem is shown in figure (7). Genetic algorithm can obtain the optimal value of coefficients vector (0.13889 ،0.23114) after 24 generations.

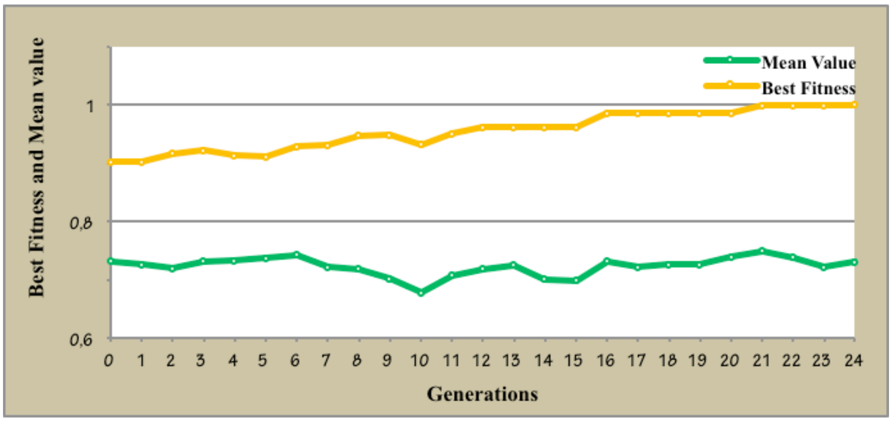

Figure 7. Progression of Genetic Algorithm (The mean value shows the average fitness values, and the best fitness indicates the highest fitness value in each generation).

It should be noted that in optimization problem, the obtained problem is not unique and with modification of initial conditions, the obtained answers will be unique and results in difference of obtained answers. But, all answers lead to optimized wavelets which can separate normal and pathological signals with 100 percent level of confidence. Also, the results of using Wavelet Daubechies-4, Daubechies-10, Coiflet-6, and Symlet-8 in the system of feature extraction are represented in table (1) which show the advantage of suggested method compared with other mother wavelets.

Table 1. Results of Optimized Discrete Wavelet and Mother Wavelets (db4, db10, coif6, sym8)

Wavelet Type	Classification Results In KAY database (%)
Optimization Wavelet Based-on Lifting Scheme	100%
Daubechies-4	90.91%
Daubechies-10	94.31%
Coiflet-6	92.63%
Symlet-8	92.41%

5. EXPERIMENTAL RESULT

In this section, the results of extracting the feature of wavelet transforms Daubechies-4, Coiflet-4, and Symlet-4 and suggested adaptive wavelet based on lifting scheme in multi-class format of 53 registered signals of normal and 194 signals of vocal cords patients individuals of Paralysis, vocal nodules, vocal fold edema, vocal fold polyp, keratosis leukoplakia, paresis using lifting scheme. One of the reasons of KAY-Elemetrics database was selected was its repetitious application in other papers and studies which enables the comparison of present studies with other methods. Another reason of selection in these diseases was their more multiplicity compared with other diseases which available in database. As shown in table (1), this method is advantageous in diagnosis of vocal cords disorder in comparison with other classifiers so that its application to find the optimal wavelet generates better results. To do a reasonable comparison between optimized wavelet system and other wavelets, wavelet Daubechies-4, Coiflet-4, and Symlet-4 with identical filter length of eight were selected and diseases were separated into two classes (table 2). Since, the bi-orthogonal wavelets have more flexibility in design; the lifting scheme was selected for generation of bi-orthogonal wavelets. As shown in table (2), the suggested method has a significantly better performance compared with other wavelets in separation of pathological signals. Therefore, due to proper performance of this method in two-class separation of vocal cords disorders, we separated these orders in three-class methods. Table (3) shows the results of these tests.

The tests enabled the separation of disorders in some groups with an acceptable accuracy. This implies that the diseases of these groups have higher potential of separation. The results of tables (2-3) show that increase in the number of diseases in different classes leads to significant results in separation of diseases which implies the suitable performance of suggested method in separation of diseases. Also on the separation of the two classes of diseases, in polyp and keratosis leukoplakia group, arrived the accuracy of the 91.04 percent, however, the use of wavelet, such as: Daubechies, Coiflet and Symlet, the accuracy of the result of not higher than 60% (table 2).

Table 4 compare the proposed method with other methods in the diagnosis of voice disorders is presented. Although these works, different diagnosis of voice has been studied, but we can see that the proposed method, compared to other methods is a significant capabilities.

Table 2. Classification results (correct rates in percentage) for 2-class groups of Six Diseases, using optimized wavelet algorithm

First disorder	Second disorder	db4	sym4	coif4	Adaptive Wavelet (Lifting Scheme)	Parameters value (c_1, c_2)
Vocal Fold Polyp	Keratosis Leukoplakia	60%	47.5%	55%	91.04%	(0.4456, 0.7592)
Keratosis Leukoplakia	Vocal Fold Edema	45.45%	47.72%	45.45%	83.43%	(0.0774, 0.3151)
Vocal Fold Edema	Paralysis	60.29%	48.52%	60.29%	70.57%	(0.8009, 0.1575)
Paralysis	Vocal Nodules	52.67%	50.89%	49.10%	80.49%	(-0.0425, -0.2956)
Vocal Nodules	Paresis	65.90%	57.98%	63.63%	69.77%	(0.9497, 0.9667)

Table 3. Classification results (correct rates in percentage) for 3-class groups of Six Diseases, using optimized wavelet algorithm

Group	Classification Results	Group	Classification Results
Edema, Polyp, Nodules	42.18%	Polyp, Nodules, Paralysis	48.56%
Edema, Polyp, Paralysis	52.11%	Polyp, Nodules, Paresis	42.12%
Edema, Polyp, Paresis	44.75%	Polyp, Nodules, Keratosis Leukoplakia	50.88%
Edema, Polyp, Keratosis Leukoplakia	53.28%	Polyp, Paralysis, Paresis	58.04%
Edema, Nodules, Paralysis	57.93%	Polyp, Paralysis, Keratosis Leukoplakia	70.14%
Edema, Nodules, Paresis	47.61%	Polyp, Paresis, Keratosis Leukoplakia	58.57%
Edema, Nodules, Keratosis Leukoplakia	60.08%	Nodules, Paralysis, Paresis	61.05%
Edema, Paralysis, Paresis	46.30%	Nodules, Paralysis, Keratosis Leukoplakia	70.88%
Edema, Paralysis, Keratosis Leukoplakia	66.27%	Nodules, Paresis, Keratosis Leukoplakia	61.21%
Edema, Paresis, Keratosis Leukoplakia	51.71%	Paralysis, Paresis, Keratosis Leukoplakia	71.28%

Table 4. Comparison of previous works and our proposed scheme

Classification Algorithm	Nayak Et Al. [16]	Vaiciukynas Et Al. [17]	Khadiviheris Et Al. [18]	Santos Carvalho Et Al. [6]	Akbari & Khalil Arjmandi [7]	Proposed Method
Feature Extraction Method	Discrete Wavelet Transform	Mel Frequency Cepstral Coefficients (MFCC)	Discrete Wavelet Packet Transform	Discrete Wavelet Transform	Discrete Wavelet Packet Transform	Adaptation Wavelet Transform By Lifting Scheme
Classifier	Artificial Neural Network (ANN)	Gaussian Mixture Model (GMM), Support Vector Machine (SVM)	Support Vector Machine (SVM), K-Nearest Neighbor's (KNN)	Multi-Layer Perceptron (MLP)	Multi-Layer Neural Network	Support Vector Machine with Radial Basis Function (RBF)
Studied Voice Disorders	Paralysis, Hyperfunction, Normal	Vocal Fold Nodules, Vocal Fold Polyp, Cyst, Normal	Unilateral Vocal Fold Paralysis, Vocal Fold Polyp, Vocal Fold Nodules, Normal	Vocal Fold Nodules Edema, Paralysis, Normal	Hyperfunction, A–P Squeezing, Gastric Reflux, Normal	Paralysis, Paresis, Vocal Fold Polyp, Vocal Fold Nodules, Edema, Keratosis Leukoplakia, Normal
Performance	80-85 (%)	90.10 (%)	91 (%)	93.33 (%)	97.33 (%)	100 (%)

6. CONCLUSIONS

In this paper, the results of applying the suggested method of transferring adaptive wavelet to lifting scheme of data were presented for two-class, three-class classifications. These classifications consist of separation between patients and normal cases (53 normal signals and 214 patient signals), separation between two classes of disease (6 cases), Separation among three classes of disease (20 cases). The analyses and obtained results lead one to conclude that the design of lifting-based adaptive wavelet in separation of samples of speech signals of normal individuals from those of patients with vocal disorders is better than other wavelets introduced ever (tables 1,4). Through application of this method, one can state the possibility of such disorders and diseases with sufficient level of confidence and provide the conditions for treatment of patients in due time. The results of table (1) also show that the present wavelet can attain the separation of normal and pathological signals of KAY-Elemetrics dataset with an accuracy of 100 percent. In regard to two-class, three-class, diagnosis of disorders, the application of optimal method can separation of disorders in some groups with an acceptable accuracy (tables 2-4). The results of present study can be used as an effective and optimal method in clinical pathology of human signal production system along with other diagnostic methods so as to increase the accuracy of diagnosis. They can also represent guidelines for application of more invasive and costly methods.

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