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Efficient hybrid speech enhancement using PCA and ANFIS for hearing aids

N. Shanmugapriya[1], Dr. E. Chandra[2]
[1]Assistant Professor, [2]Director
[1,2] Dr. SNS Rajalakshmi College of Arts and Science
[1]Coimbatore -641 049, INDIA
[1]Email: spriyanatrajan@gmail.com

Abstract- More commonly, digital hearing aid user's make complaint regarding the complicatedness in understanding the speech in existence of background noise, which is still unresolved. In order to enhance the speech perception in a noisy atmosphere, several speech enhancement approaches have been formulated in digital hearing aids. But still there is no efficient technique to overcome this setback. In this research work, a speech enhancement algorithm is proposed for digital hearing aids. This scheme includes preprocessing, feature extraction and noise reduction block. The algorithms such as Principal Component Analysis (PCA) based Adaptive Neuro Fuzzy Inference System (ANFIS) is proposed in this research for enhancing the speech for digital hearing aids. A proposed speech enhancement algorithm is presented for the purpose of enhancing the speech intelligibility in noise for the near-end listener. Experimentation results of the proposed algorithm are compared with the existing spectral subtraction, wiener filter and genetic SVD based on SNR and PESQ, and it shows that the performance of the proposed algorithm is better than the existing approaches.

Keywords- Speech enhancement, Hearing aid devices, Principal component analysis, Gaussian noise.

1. Introduction

Huge quantity of speech related applications like cellular mobile communication and hearing aid devices, speech enhancement and noise reduction, automatic voice recognition and speaker authentication systems, is turning out to be an important research topics, that requires for pre-processing the speech signal for further process[1].

In hearing aid instrument, the users habitually have immense trouble in understanding the speech in a noisy atmosphere. They normally necessitate a signal-to-noise ratio (SNR) of about 5–10 dB more than normal hearing listeners to realize the similar level of speech understanding. As a result, numerous single- and multi microphone noise reduction schemes have been formulated for modern hearing aids. Multi microphone noise reduction schemes are capable of exploiting spatial together with spectral information and are consequently preferred to single-microphone systems [2].

There are two significant objects often essential to be taken care in speech enhancement applications are eradicating the undesired noise from the speech to enhance the Signal-to-Noise Ratio (SNR), and retrieving the superiority of the original speech signal which leads to enhancement of the speech intelligibility. As a result, there could be a trade-off among the residual noise together with the speech quality in a speech improvement application and the accomplishment of the speech enhancement techniques typically based on satisfying both the objective and subjective targets. In fact, it is extremely complicated or even impractical to satisfy all of the targets simultaneously [3].

Digital technology has made an imperative involvement in the field of audiology. Digital signal processing approaches provide enormous potential for devising a hearing aid however, present digital hearing aid are not equal to the anticipation for sensorineural loss patients. Hearing-impaired patients applying for hearing aid disclose that in excess of 50% are because of sensorineural loss. As a result, only adaptive filtering approaches are appropriate for the reduction of noise from the speech signal for sensorineural loss patients [4].

On the other hand, the noise reduction schemes presently employed in recent hearing aids specially adaptive directional noise reduction systems, are intended to optimize speech in noise monaurally [5,6]. In a bilateral hearing aid design, these schemes do not consider the contralateral ear and consequently possibly will inaccurately represent the binaural cues [7].

In multichannel speech enhancement scheme, direction of arrival (DOA) is a strong cue by which to isolate a preferred signal. If the approximate DOA of the objective signal is predetermined then processes for assessment of optimal real-valued [8] or complex [9] spatial filters can be obtained. In the nonexistence of a predetermined DOA, following the spatial and spectral statistics of the objective and noise sources can be exploited to obtain spatial filters [10]. On the other hand, employing DOA possibly will have unwanted inferences in dynamic atmospheres when the relative position of sound sources can transform quickly (i.e. because of source or head movements), or when a additional source of interest comes into view from an indefinite direction.

Another method is to carry out binaural speech enhancement by means of spectral weighting. In these circumstances, a beamformer is not utilized for speech enhancement by beamsteering, however to drive the spectral weight computation as given in [11] for binaural cue preserving speech dereverberation. A delay-and-sum beamformer (DS BF) is exploited to acquire an averaged 'reference signal' of the left and right HA signal from which the Power Spectral Density (PSD) of late reverberant speech for the spectral weight computation is estimated. On the other hand, the beamformer scheme, including the desirable source localization, for such functions is subject to difficult design constraints.

Until now, existing speech enhancement approaches accomplishes only a low degree of suppression of speech distortions owing to room reverberation. Such destructions are caused by the numerous reflections and diffraction of the echo on walls and things in a room. These multiple echoes append to the direct sound at the receiver and distort its temporal and spectral features. Accordingly, reverberation and background noise considerably diminish listening comfort and speech clearness, particularly for hearing impaired persons. For that reason, in this research work, in order to surpass the aforementioned complications in current digital speech enhancement techniques, the algorithm is proposed for enhancing the speech signal obtained from the microphone is enhanced and it is discussed briefly in the following sections.

2. Related Works

Den Bogaert et al., (2007) [12] discussed the binaural cue conservation of a noise elimination algorithm for bilateral hearing aids, specifically the multichannel Wiener filter with inter aural transfer function extension (MWF-ITF). An additional name was included to the cost function to conserve the binaural cues of the speech and noise component of a signal at the cost of a quantity of noise reduction. The author integrated the theoretical investigation along with objective binaural performance metrics and a perceptual assessment.

A speech pre-processing approach was formulated in [13] to enhance the speech clearness in noise for the near-end listener. This approach enhances the clearness through the process of optimally redistributing the speech energy after a while and frequency in case of a perceptual deformation measure, which depends on a spectro-temporal auditory model. In contradiction of spectral-only models, short period information was considered. Accordingly, this approach was more responsive to transient areas, which will hence obtain more amplification compared against stationary vowels. It was recognized from literature that varying the vowel-transient energy ratio was helpful for enhancing speech-intelligibility in noise.

In [14], binaural cue preserving speech enhancement system was formulated depending on spectral weighting [14]. The beamformer can be exploited as delay-and-sum and/or delay-and-subtract to offer subband signals from which the power spectral densities of interfering sources can be approximated to obtain the spectral weight computation. A beamformer for binaural speech enhancement schemes in digital hearing aids was employed. Its single modules for the evaluation of the Time-Difference-Of-Arrival (TDOA) and time-alignment function in the frequency-domain and have a small computational complication. The TDOA evaluation is carried out efficiently by a generalized cross-correlation with phase transform weighting. The assessment accuracy for filter-banks with a restricted number of subbands, which are required for hearing aids to satisfy tight delay constraints, was enhanced by a histogram-based TDOA estimation. The succeeding time-alignment is achieved by an uncomplicated multiplication with spectral phase factors.

In [15], the author discussed the approaches in a hearing aid application for exploiting the directionality of sound energy as a decisive factor to approximate single- and multichannel linear filters for betterment of the speech signal by eliminating the diffuse noise and also reverberation. The author evaluated the conservative strategies where direction of arrival is unidentified and more forceful strategies where the speech techniques can be exploited to obtain a quick acting post-filter for the perfect productivity of a beamformer. Here, they revealed that in certain circumstances where a target of significance is closer to the listener at the same time interfering sources are further apart, uncomplicated characteristics that get hold of the directionality of sound energy can be exploited to attenuate significant undesired signal energy and can be more efficient when compared to a strategy using noise-floor tracking.

The author in [16] recommends speech enhancement in binaural multimicrophone hearing aids by noise reduction algorithms depending on the Multichannel Wiener Filter (MWF) and the MWF with fractional noise estimate (MWF-N). Both approaches are exclusively formulated to integrate noise reduction with the conservation of binaural cues. Purpose and perceptual assessments were carried out with several speech-in-multitalker-babble configurations in two dissimilar acoustic atmospheres. The major findings are: (a) A bilateral MWF with great voice activity recognition equals or do better than a bilateral adaptive directional microphone based on speech enhancement, furthermore it helps to in preserve the binaural cues of the speech component. (b) A noteworthy increase in speech enhancement is found when transmitting one contralateral microphone signal to the MWF active at the ipsilateral hearing aid. Adding together a second contralateral microphone demonstrated a considerable development at some stage in the objective evaluations however not in the subset of situations tested in the period of the perceptual evaluations. (c) Adding the fractional noise approximate to the MWF, completed to enhance the spatial awareness of the hearing aid user, decreases the quantity of speech enhancement in a restricted manner. In certain situations, the MWF-N even does better than the MWF perhaps because of an improved spatial release from masking.

The author in [17] formulated a novel sound source separation approach for binaural speech enhancement depending on supervised machine learning and time-frequency masking. The scheme was intended by taking the power restrictions in hearing aids into account, limiting mutually the computational cost and transmission bit rate. Transmission plan is optimized with the help of a tailored evolutionary approach that allocates a dissimilar amount of bits to all frequency bands. This scheme necessitates below 10% of the accessible computational resources for the purpose of signal processing and acquires good separation performance with the assistance of bit rates lower than 64 kbps.

The significance of accurate noise estimation is explained in [18], in terms of speech enhancement in the field of hearing aids. The speech signal in various atmospheres, for instance, restaurant, bus, train and car are regarded as input. Clean speech signals are distorted by background noise correspondingly restaurant noise, car engine noise and train noise at three dissimilar SNR levels 0dB, 5dB, 10dB. Here, three dissimilar methods are exploited to approximate the noise. One is Voice Activity Detector (VAD), second is Martins noise estimation approach and third is MCRA-2 noise estimation approach. Modified spectral subtraction approach is exploited for speech enhancement.

3. Background

3.1. Principal Component Analysis

Principal Component Analysis (PCA), a linear transform which is an extremely efficient way of obtaining features. It is effectively implemented to several applications of pattern recognition. Consider N and t represent the number of samples and their dimension of dataset D, correspondingly. PCA discovers a subspace whose basis vectors characterize the maximum-variance direction of the original space. Consider W indicates the linear transformation that maps the original t-dimensional space into an f-dimensional feature space where usually $f \ll t$. Equation (1) reveals the new feature vectors, $z_j \in R^f$,

$$z_j = W^T x_j, j = 1,2, \dots, N \quad (1)$$

Columns of W are the Eigen vectors e_j which is obtained by solving (2):

$$\lambda_j e_j = Qe_j \text{ where } Q = XX^T, X = \{x_1, \dots, x_N\} \quad (2)$$

At this point, Q represents the covariance matrix and λ_j indicates the Eigen value related with the Eigen vector e_j. The Eigen vectors are arranged from high to low in accordance with their equivalent Eigen values. The Eigen vector related with biggest Eigen value is the most significant vector that reflects the maximum variance.

PCA utilizes the complete characteristics and it obtains a collection of projection vectors to obtain global feature from given training samples. The performance of PCA is condensed in case of more inappropriate features than the appropriate ones. In contrast, PCA contains no pre knowledge regarding the class in a specified data. As a result, it is not capable to decide the classes in the subspace of a given dataset.

3.2. ANFIS Architecture

ANFIS configuration is a oversimplified neural network by means of a Sugeno fuzzy model, as demonstrated in Fig. 2. Nodes at the equivalent layer have comparable functions. The output of the ith node in layer l is indicated as $O_{l,i}$.

Layer 1: Each node i in this layer is an adaptive node with a node function,

$$O_{l,i} = \mu A_i(x) \text{ for } i = 1,2 \text{ or} \quad (3)$$

$$O_{l,i} = \mu B_{i-2}(x) \text{ for } i = 3,4 \quad (4)$$

where x (or y) represents the input to the ith node and A_i (or B_{i-2}) indicates a linguistic label (such as “low” or “high”) related with this node. It means, $O_{l,i}$, represents the membership grade of a fuzzy set A ($= A_1, A_2, B_1, \text{or } B_2$) and it indicates the degree to which the given input x (or y) satisfies the quantifier A . The membership functions for A and B are typically described by generalized bell functions, e.g.:

Here $\{a_i, b_i, c_i\}$ represents the parameter set. Since the values of these parameters vary, the bell-shaped function differ consequently, exhibiting several forms of membership functions on the linguistic label A_i. The figure 1 explains the first order sugeno fuzzy model with two rules. Indeed, some continuous and piecewise differentiable functions, such as the universally employed triangular shaped membership functions, are also competent candidates for node functions in this layer. Parameters in this layer are indicated as premise parameters. The outputs of this layer are the membership values of the premise part.

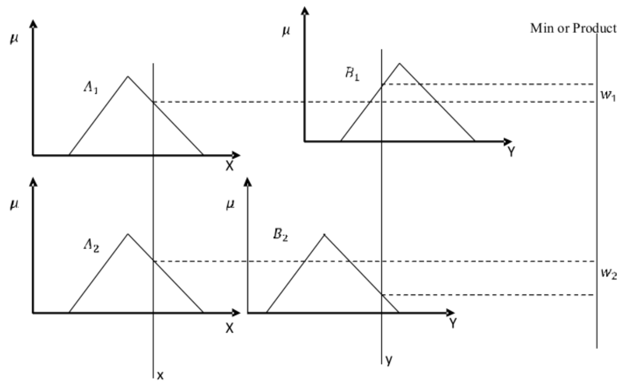

Fig 1:Two-input first-order Sugeno fuzzy model with two rules

Layer 2: This layer includes the nodes labeled $\prod$ which multiply incoming signals and gives the product out. For example,

$$O_{l,i} = w_i = \mu A_i(x) \mu B_i(y) \; i = 1,2 \quad (5)$$

Every node output indicates the firing potency of a rule.

Layer 3: In this layer, the nodes tagged N compute the ratio of the ith rule’s firing power to the sum of the entire rules’ firing strengths,

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \; i = 1,2 \quad (6)$$

The outputs of this layer are called the normalized firing strengths.

Layer 4: This layer’s nodes are adaptive with the following node functions,

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \quad (7)$$

where $\overline{w}_i$ represents the output of layer 3, and $\{p_i, q_i, r_i\}$ indicates the parameter set. Parameters of this layer are referred to as resultant parameters.

Layer 5: This layer’s single predetermined node, labeled $\sum$, works out the final output as the summation of the entire incoming signals which is as follows,

$$O_{5,i} = \sum_{i=1} \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (8)$$

As a result, an adaptive network that is functionally corresponding to a Sugeno first-order fuzzy inference system is generated. The architecture of ANFIS is shown in Fig. 2.

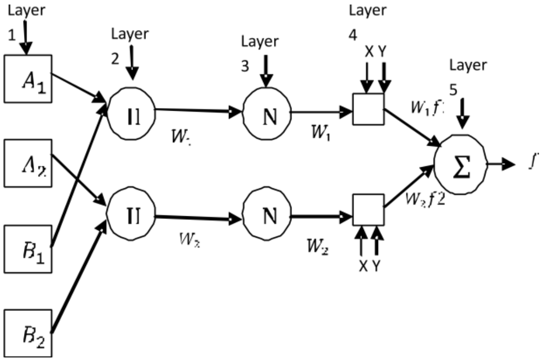

Fig 2: Equivalent ANFIS Architecture

4. Proposed Methodology

In this research, a novel hybrid speech enhancement approach is proposed for the betterment of the speech signal for hearing aids in various atmospheres. The existing approaches have numerous setbacks at some point in speech enhancement. In order to surpass these setbacks in the existing approaches, the proposed algorithm exploits principal component analysis and adaptive neuro fuzzy inference system for comprehensively reducing the noise. The overall flow diagram of proposed methodology to filter the noise from original speech signal is shown in the figure 3.

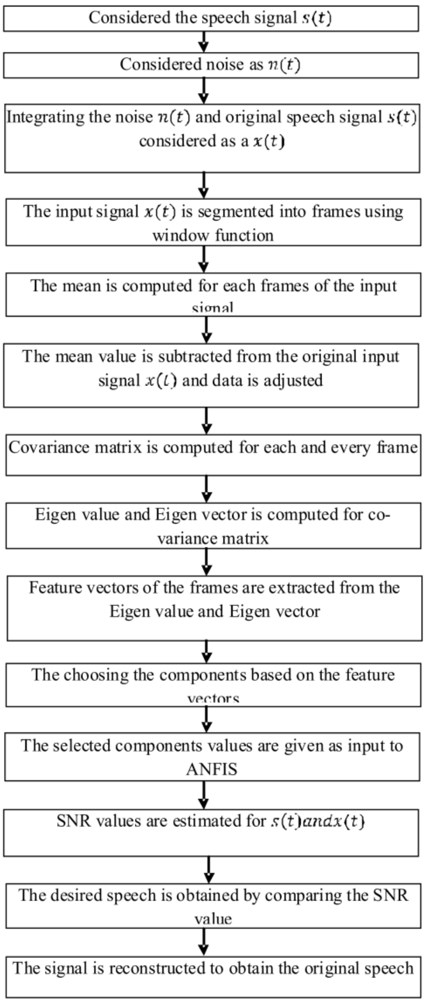

Fig 3: The flow diagram for Hybrid PCA process

4.1. Principal Component Analysis

Principal components analysis (PCA) is a kind of approach employed to lessen noise and enhancing the speech signal for analysis [19]. PCA includes computation of the Eigen value decomposition or singular value decomposition of a speech signal, typically following mean centering the data for each attribute. PCA engages a mathematical process that converts a number of correlated variables of signal into a number of uncorrelated variables called principal components [20, 21].

Assume a speech signal $s(t)$ distorted by noise $n(t)$. The white, pink, babble is some kind of noise taken into account here. The observed noisy signal can be given as follows:

$$x(t) = s(t) + n(t) \tag{9}$$

An extremely well-organized and robust execution of the subspace approach is offered by the PCA of the following m-dimensional vector, and the speech signal is transformed into m frames which are extracted by an embedding in the space of the delayed coordinates:

$$x(t) = [x(t), x(t-1), \dots, x(t-\text{lag})]^T \tag{10}$$

$$t = \text{lag}, \dots, N-1$$

Where N represents the frame size, $m = (\text{lag}+1)$ represents the embedding dimension and lag has to be selected to acquire an optimal value for m. the mean value of the each frames are computed by means of the formula given below,

$$\text{mean} = \frac{1}{n}\sum_{k=1}^{n} x_k(t) \tag{11}$$

When the computation of mean value in the proposed system is completed then the entire frames are fine-tuned in accordance with the calculated mean vector. PCA discovers a subspace whose basis means vectors characterize the maximum-variance direction of the original space. The covariance matrix of the input frames are computed with the help of the mean vector and the formula for the covariance calculation is provided below,

$$S = \sum_{k=1}^{n}(x_k - m)(x_k - m)^T \tag{12}$$

Where m indicates the mean vector. The Eigen value and Eigen vector for speech frames are computed in accordance with the covariance matrix. The formula employed for computing the Eigen value and Eigen vector is provided below,

$$\lambda_j e_j = S e_j \text{ where } S = \sum_{k=1}^{n}(x_k - m)(x_k - m)^T, x = \{x_1, \dots, x_N\} \tag{13}$$

At this point, S represents the covariance matrix and λ_j represents the Eigen value connected with the Eigen vector e_j. The Eigen vectors are organized from high to low in accordance with their equivalent Eigen values. The Eigen vector related with biggest Eigen value is the most vital vector that reflects the utmost variance [22, 23]. As a result, the projected data is worked out with the help of $Y = XE$, in which $E = [e_1, \dots, e_m]$ represents a $d \times m$ matrix where the columns e_j indicates the Eigen vectors along the lines of the biggest m Eigen values.

Once the Eigen value and Eigen vector is computed then the constituent s from the entire frame is chosen using the Eigen value and Eigen vector. The characteristics of the constituent are also chosen with the help of Eigen vector where it utilizes the complete features and it gets a collection of projection vectors to extract global feature from provided training samples.

4.2. Classification of signal using ANFIS

In layer 1, the constituents obtained from the PCA are provided as an input. The values are transformed into the fuzzy set in the layer 1. In layer 2, SNR is calculated approximately for the entire constituent with the help of the feature vectors extracted from the PCA and it is regarded as $\hat{x}(t)$ SNR value of the original input signal (speech signal+noise) $x(t)$ and $y(t)$ is SNR value of the original speech signal $s(t)$. In layer 3, in accordance with the SNR values the preferred speech signal is obtained from the entire fuzzy set. In layer 4, the fuzzy set is transformed into the original signal with the help of the process called defuzzfication process. The acquired signal from each component is summarized into original signal into layer 5.

SNR estimation is given as follows,

$$\mathrm{SNR} = 10\log\frac{\sum_{k=1}^{n} s^2(n)}{\sum_{k=1}^{n}(s(n)-\hat{s}(n))^2} \qquad (14)$$

4.3. Proposed algorithm

Following steps forms the hybrid algorithm for reducing noise from speech signal with the help of PCA-ANFIS

Step 1: Obtain the noisy signal $x(t)$ from hearing aids.

Step 2: The observed signals $x(t)$ are segmented into n frames by the application of a window function.

Step 3: Work out the mean value of for a given signals equ.11

$$\mathrm{mean} = \frac{1}{n}\sum_{k=1}^{n} x_k(t)$$

Step 4: Subtract the mean and get data fine-tuned.

Step 5: Compute the covariance matrix with the help of the mean value of the input the signal. Equ.12

$$S = \sum_{k=1}^{n} (x_k - m)(x_k - m)^T$$

Where m represents the mean vector

Step 6: Work out the Eigen vector and Eigen value for the covariance matrix.

If S represents a covariance matrix, a non zero vector v indicates the Eigen vector of S, if there is a scalar λ(eigenvalue) such that, equ.13

$Sv = \lambda v$

Step 7: Consequently the projected data is computed with the help of $Y = XV$ where $V = [v_1, \ldots, v_m]$ represents a $d \times m$ matrix where the columns v_i indicates the Eigen vectors along the lines of the biggest m Eigen values.

Step 8: Deciding the constituent depending on the projected data using the computed Eigen value and Eigen vector and builds a feature vector with the assistance of the Eigen values.

Step 9: SNR is calculated approximately for the entire constituent obtained from the previous step and also SNR $y(t)$ is estimated for original signal $s(t)$ in ANFIS.

Step 10: in accordance with the SNR, the ANFIS is trained to categorize the original signal from noise signal

$\hat{s}(t) = \hat{x}(t) - y(t)$

5. Experimental Results

The experimental evaluation of the proposed technique and its real time execution was performed with the help of informal listening and objective evaluation with the help of Perceptual Evaluation of Speech Quality (PESQ) measure [24]. The impulse response was obtained from the RWCP sound scene database [25]. This objective measure is a prediction of the subjective Mean Opinion Score (MOS) of the corrupted speech and is computed from the variation among the loudness spectra of level-equalized and time aligned original and degraded signals. The proposed speech enhancement is evaluated against the existing algorithm such as, spectral subtraction [26], wiener filter [27] and genetic SVD [28].

In this research work, testing process is involved by processing the speech with the existence of additive white, pink, babble. An objective evaluation of the outputs from Matlab based implementation was performed using PESQ measure for three categories of noise and SNR circumstances.

Figure 4 and table 1, compares the SNR values for white noise of the hybrid PCA-ANFIS against the existing approaches such as spectral subtraction, wiener filter and genetic SVD. It is observed that the hybrid PCA-ANFIS achieves the maximum SNR whereas other algorithms had the lowest SNR value.

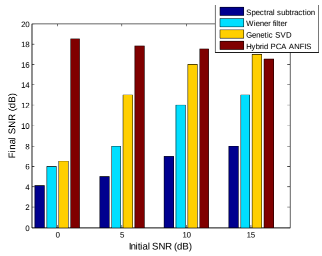

Fig 4: Comparison of SNR values for white noise

Table 1: Comparison of SNR Values for white noise

SNR	Spectral Subtraction	Wiener	Genetic SVD	Hybrid PCA-ANFIS
0	4.1	6	6.5	18.2
5	5	8	13	17.6
10	7	12	16	17.1
15	8	13	17	16.8

Figure 5 and table 2, compares the PESQ values for white noise of the hybrid PCA-ANFIS against the existing approaches such as spectral subtraction, wiener filter and genetic SVD. It is observed that the hybrid PCA-ANFIS achieves slightly higher PESQ whereas other algorithms had the lowest PESQ value.

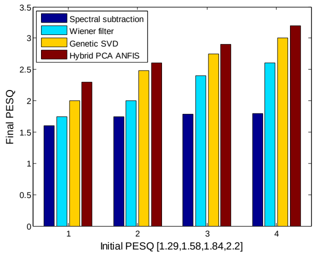

Figure 5: Comparison of PESQ values for white noise

Table 2: comparison of PESQ values for white noise

PESQ	Spectral Subtraction	Wiener	Genetic SVD	Hybrid PCA-ANFIS
1.29	1.6	1.75	2	2.3
1.58	1.75	2	2.48	2.6
1.84	1.79	2.4	2.75	2.9
2.2	1.8	2.6	3	3.2

Figure 6 and table 3, compares the SNR values for different noises such as white noise, pink and babble of the hybrid PCA-ANFIS against the existing approaches such as spectral subtraction, wiener filter and genetic SVD. It is observed that the hybrid PCA-ANFIS achieves the better SNR whereas other algorithms had the lowest SNR value.

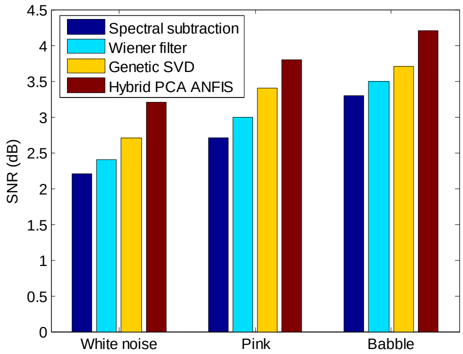

Fig 6: SNR comparison for different noise

Table 3: Comparison of SNR values for different noises

Types of noise	Spectral subtraction	Wiener filter	Genetic SVD	Hybrid PCA-ANFIS
White noise	2.2	2.4	2.7	3.2
Pink	2.7	3	3.4	3.8
Babble	3.3	3.5	3.7	4.2

Figure 7 and table 4, compares the PESQ values for different noises such as white noise, pink and babble of the hybrid PCA-ANFIS against the existing approaches such as spectral subtraction, wiener filter and genetic SVD. It is observed that the hybrid PCA-ANFIS achieves slightly higher PESQ whereas other algorithms had the lowest PESQ value.

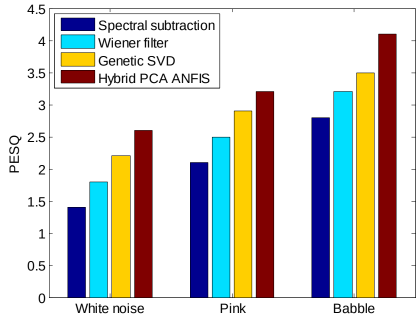

Fig 7: PESQ comparison for different noise

Table 4: Comparison of PESQ values for different noises

Types of noise	Spectral subtraction	Wiener	Genetic SVD	Hybrid PCA-ANFIS
White noise	1.4	1.8	2.2	2.6
Pink	2.1	2.5	2.9	3.2
Babble	2.8	3.2	3.5	4.1

6. Conclusion

Speech enhancement looks to eradicate noise in diverse surroundings, the most prominent of which are telecommunications applications. Subsequent to numerous research works there is no faultless solution exists to solve the speech enhancement setback. In this research work, a new algorithm is presented for the purpose of effective speech enhancement. Here, the influence of noise is considerably reduced using the hybrid principal component analysis based on Adaptive neuro fuzzy inference system. The performance evaluation based on SNR and Perceptual Evaluation of Speech Quality (PESQ) tests for different noise such as white, babble and pink, which shows clearly that proposed algorithm provides some signal distortion and a higher noise reduction using the hybrid PCA-ANFIS algorithm.

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