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Implementation of NKAP Algorithm for Speech Enhancement

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ABSTRACT

The aim of our research is to implement NKAP algorithm for enhancement the speech in noisy communication medium. It is important to remove the background noise in most of the applications like recognition of speech, telephonic conversations, bio medical applications like hearing aids, investigative applications forensic applications etc. kernel adaptive filters are used for removal of noise due to their good performance. If the noise signal is more stationary than the speech ie. More slowly than the speech it is easy for us to identify the noise in the speech during pauses. Or else it will be very strenuous for us to identify the noise which effects the quality of the speech i.e degradation of speech. In order to enhance the quality and comprehensibility of speech, far apart from time and frequency domains, we can process the speech signal in advanced domain like Reproducing Kernel Hilbert Space (RKHS) for great dimensional to get more powerful nonlinear extensions. We have used the Noisy Speech Corpus Database (NOIZEUS) to perform the experiments. In the results it is observed that removal of noise in RKHS has better performance in SNR values when compared with Conventional Adaptive filters.

Keywords: APA, KAPA, NKAP, RKHS, NOIZEUS, Speech enhancement

1. INTRODUCTION

Adaptive filtering is one of the major subfield of digital signal processing on which active research is going on from more than fifty years and having major significance in cancellation of noise and identification of system etc. in such systems which are relevant for removal of noise the characteristics of the signal are quite faster rate. Now a days the research on adaptive filters concentrated on high dimensional to get strong nonlinear relevance of the signals. It was done uncomplicated by using Kernel adaptive filters through Reproducing Kernel Hilbert Space. The justification for this approach has been given due to dissimilarity of SNR across the speech spectrum.

Unlike the White Gaussian noise (WGN) contains a flat spectrum, however the world noise spectrum isn't flat. Thus, the impact of noise signal over speech signal is non-uniform over the complete spectrum. Some area unit affected additional adversely than the opposite frequencies. In multi-talker babble, most of the speech energy resides at the low frequencies, area unit affected over the high frequencies. therefore to estimate an acceptable issue that may deduct simply the required quantity of the noise spectrum from every frequency bin (ideally) becomes imperative, to stop corrosive subtraction of the speech whereas residual noise reduction. An extra issue that results in variation in SNR is that the undeniable fact that noise has random impact on completely different vowels and consonants.Due to the random nature of the noise and therefore the inherent complexities of speech signal, it's harder to urge obviate varied varieties of noise. Noise reduction techniques sometimes have a exchange between the quantity of noise removal and speech distortions. Several noise reduction algorithms are projected to scale back the noise impact for speech

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sweetening, for instance, spectral subtraction (SS), Wiener filtering, minimum mean sq. error (MMSE) based mostly speech estimation, kalman filtering and Bayesian based mostly estimation etc.

Section 1 gives introduction about our research, section 2 deals with speech enhancement, section 3 briefs about adaptive filters, section 4 gives information about kernel adaptive filters, section 5 shows experimental results, section 6 analyzes the performance of my research and section 7 concludes my paper.

2. SPEECH ENHANCEMENT

Speech improvement could be a difficult task in several applications like hearing aids, rhetorical applications, military, cellular environments, front-ends for speech recognition system, telecommunication signal improvement, etc. it's merely the development in comprehensibility and/or quality of a degraded speech signal by victimization signal process tools. By speech improvement, it contains not solely noise reduction however conjointly to dereverberation and separation of freelance signals.

Speech improvement could be a basic for analysis within the applications of digital signal process. Speech improvement could be a terribly tough downside principally for 2 reasons. Firstly, the characteristics and nature of the noise signals will modification dramatically in time and for numerous applications and conjointly to search out corresponding algorithms that basically add numerous sensible environments. Secondly, for every application, the performance live may be outlined otherwise. the subsequent Figure 1 shows basic plan of speech improvement.

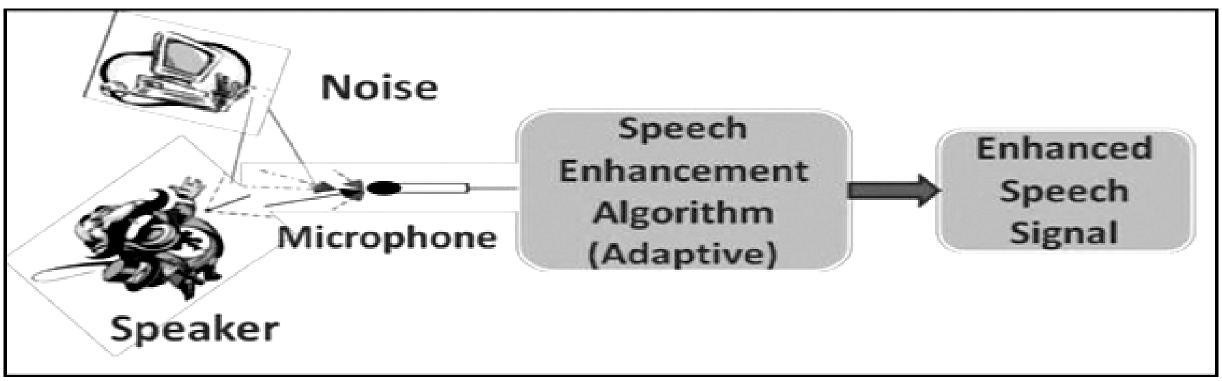

Figure 1: Basic Plan of Speech Improvement

3. ADAPTIVE FILTERS

Whenever there are either unknown fixed specifications or unsatisfied specifications by time-invariant filters, an adaptive filter is needed. Since the characteristics are keen about the input signal, an adaptive filter may be a nonlinear filter and consequently the homogeneity and additivity conditions aren't satisfied. adaptive filters are time-varying since filter parameters are continually dynamic to satisfy performance requirement. adaptive filters are effective and widespread approaches for the speech improvement.

Before starting the APA, KAPA and NKAPA, an adaptive filter introduction is given as follows. The name "adaptive filters", adjective adaptive can be empathized by considering the system that tries to adjust itself so on respond to some encompassing development. In other words the system tries to adjust its parameters with an aim of meeting some well outline target that depends on system state as well as its encompassing. moreover there's a requirement to possess bound procedure by that the method of adaptation is dole out. and eventually the system that undergoes the method of adaptation is named by the a lot of technical name "filter".

The adaptive filter has benefits like lower process delay and better tracking of the trajectory of non-stationary signals [2]. These are essential characteristics in applications like noise estimation, echo cancellation, adaptive delay estimation and channel leveling, wherever low delay and quick wrenching of time-varying environments and time-varying processes are necessary objectives.

The existence of a reference signal that is hidden within the fixed-filter approximation step, defines the performance criterion. the overall adaptive-filter configuration is shown in figure 2.

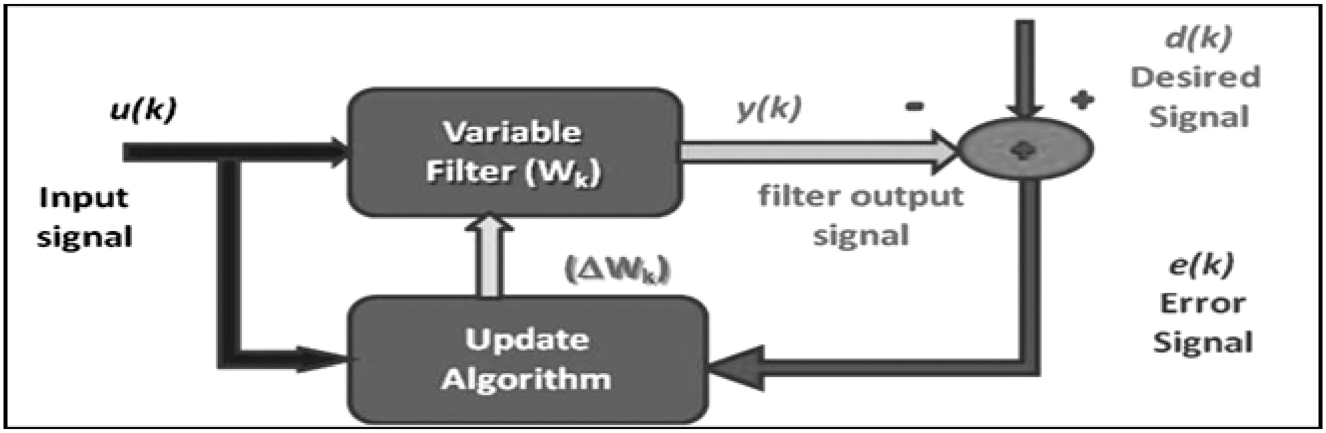

Figure 2: overall adaptive-filter configuration

An adaptive filter is specified as

$$y(k) = w^T(k)\, u(k) \tag{1}$$

Where k is that the time index, y is that the filter output, x the filter input, W_k are the filter coefficients. The diagram, shown within the following figure 2, is a foundation for explicit adaptive filter realization [11], like Affine Projection algorithmic rule (APA). The theme behind the overall configuration is that a variable filter that extracts associate estimate of the required signal.

The following assumptions were made:

Input signal u(k) = desired signal d(k) + intrusive noise v(k)

$$u(K)= d(k)+ v(k) \tag{2}$$

The variable filter has a Finite Impulse Response (FIR) structure. i.e. for such structures the impulse response is adequate to the filter coefficients. For a filter of order p, the coefficients are outlined as

$$Wk = [Wk\,(0), Wk\,(1), \,.\,.\,.\,.\,.\, Wk\,(p)] \tag{3}$$

The distinction between the required and therefore the calculable signal is that the error signal or price operate

$$e(k) = d(k) – y\,(k) \tag{4}$$

The variable filter can estimates the required signal by convolving the signal beside the impulse response. The expression in vector notation as

$$y\,(k) = W_k * u(k) \tag{5}$$

Where

$$u(k) = [u(k), u(k – 1),...u(k – p)] \tag{6}$$

is associate signal vector. Moreover, the variable filter updates its coefficients at each instant of your time

$$W_{k+1} = W_k + DW_k \tag{7}$$

Where ΔW_k could be a correction issue for the filter coefficients. supported the input and error signals, the adaptive algorithmic rule generates this correction issue.

3.1. Affine Projection Algorithm (Apa)

Affine Projection algorithmic rule (APA) [10] was derived as a generalization of the NLMS algorithmic rule. In APA, the projections were created in multiple dimensions wherever jointly dimensional in NLMS, within the sense that every faucet weight vector update of the NLMS is viewed as a 1 dimensional affine projection, whereas within the APA multiple dimensional projections were created. As increasing the projection dimension, will increase the convergence rate of the faucet weight vector. However, it results in redoubled machine complexness.

Let d (desired signal) be a zero-mean scalar-valued variate and let u (noisy signal) be a zero-mean $L \times 1$ variate with a positive-definite variance matrix $R_u = E[uu^T]$. The cross-covariance vector of d and u is denoted by by$r_{du} = E[du]$. the burden vector w that solves

$$\mathrm{Min}_w \, (E\,|d - w^T u|^2) \tag{8}$$

is given by $w^0 = R_u^{-1} r_{du}$ [3].

Several ways that approximates w iteratively conjointly exist. As an example, the common gradient methodology

$w(0)$ = initial guess;

$$w(k) = w(k-1) + \eta[r_{du} - R_u\, w(k-1)] \tag{9}$$

or the regularized Newtons formula,

$w(0)$ = initial guess;

$$w(k) = w(k-1) + \eta(R_u + \varepsilon I)^{-1}\, [r_{du} - R_u\, w(k-1)] \tag{10}$$

Where ε may be a little positive regularization issue and η is that the step size nominative by designers. Stochastic-gradient algorithms replace the variance matrix and therefore the cross-covariance vector by native approximations directly from information at every iteration. To get such approximations, many ways in which square measure accessible. The trade-off is convergence performance, computation complexness and steady-state behavior [3].

Assuming that we've access to random variables (d and u) observations over time and The Least-mean-square (LMS) algorithmic rule merely uses the fast values for approximations

$$\hat{}Ru = u(k)u(k)^T \text{ and } \hat{}rdu = d(k)u(k).$$

The corresponding steepest-descent formula (9) and Newtons formula (10) become

$$w(k) = w(k-1) + \eta u(k)[d(k) - u(k)^T w(k-1)] \tag{11}$$

$$w(k)=w(k-1)+\eta u(k)[u(k)^T u(k)+\varepsilon I]^{-1}[d(k)-u(k)^T w(k-1)] \ (12)$$

The affine projection algorithmic rule but employs higher approximations. Specifically, the approximations R_u and rdu square measure replaced by the fast approximations from the K most up-to-date regressors and observations. Denoting

$$U(k) = [u(k-K+1), ..., u(k)]_{LxK} \text{ and}$$
$$d(k) = [d(k-K+1), \ldots, d(k)]^T$$

one has

$$\hat{}R_u = (1/K)U(k)U(k)^T \text{ and } \hat{}r_{du} = (1/K)\, U(k)d(k) \tag{13}$$

Therefore (9) and (10) become

$$w(k) = w(k-1) + \eta U(k)[d(k) - U(k)^T w(k-1)] \tag{14}$$

3.2. Normalized Affine Projection Algorithm (Napa)

The normalized affine projection algorithmic program becomes

$$w(k) = w(k-1)+\eta[U(k)TU(k)+\varepsilon I]\text{-}1\ U(k)\ldots.$$
$$\ldots..[d(k)-U(k)Tw(k-1)] \tag{15}$$

and (15), by matrix operation lemma, is resembling [3]

$$w(k)=w(k-1)+\eta U(k)[U(k)TU(k)+\varepsilon I]\text{-}1\ldots..$$
$$\ldots.[d(k)-U(k)Tw(k-1)] \tag{16}$$

It is noted that this equivalence lets us. modify the matrix [U(k)T U(k) + εI] rather than [U(k)U(k)T + εI] and it plays a really necessary role within the derivation of kernel extensions. we tend to decision rule (14) APA and rule (16) normalized APA.

4. KERNEL ADAPTIVE FILTERS

Kernel method is a good nonparametric modeling technique. The main theme of kernel method is to transforming the input data into a high dimensional feature space through a reproducing kernel such that the inner product operation can be computed efficiently in the feature space through the kernel evaluations [5]. After that an appropriate linear methods are subsequently applied on the transformed data.

As long as an algorithm can be formulated in terms of equivalent kernel evaluation (or inner products), there is no call to perform computations in the high dimensional feature space. This is the main advantage when compared to the traditional methods. Successful examples of this methodology include kernel principal component analysis, support vector machines (SVM's), etc. The SVM's have already shown good functioning in increasing the accuracy of speech recognition activity.

Kernel adaptive filters are online kernel methods, closely related to some artificial neural networks such as radial basis function networks and regularization networks[6]. The kernel adaptive filtering technique used in this work for general nonlinear problems. It is a natural generalization of linear adaptive filtering in reproducing kernel Hilbert spaces.

4.1. Kernel Affine Projection Algorithm (Kapa)

A kernel [11] may be a radially symmetrical, continuous, positive-definite perform ^{k} : U × U → R.. U is that the input domain, a compact set of RL. The ordinarily used kernels embody the mathematician kernel (17) and therefore the polynomial kernel (18):

$$k\,(u, u2\,) = \exp\,(-a\|u - u'\,\|^2) \tag{17}$$
$$k\,(u, u') = (u^T\,u' + 1)^P \tag{18}$$

Steps concerned in kernel affine projection algorithmic program square measure as follows

Algorithm: Kernel Affine Projection Algorithm (KAPA)

Initialization:

learning step η

$$a_1\,(1) = \eta\ d(1) \tag{19}$$

while {u(k), d(k)} available do

% apportion a replacement unit of weight vector

$$a_k(k-1) = 0 \tag{20}$$

for n = max(1, k – K + 1) to k do

% evaluate outputs of this network k-1

$$y(k,n) = \sum_{j=1} a_j (k\text{-}1) k_{n,j} \tag{21}$$

k is the kernel function.

.

% computer errors

$$e(k, n) = d(k) – y(k, n) \tag{22}$$

% update the min(k, K) most up-to-date units

$$a_n (k) = a_n(k – 1) + \eta\, e(k, n) \tag{23}$$

end for

if k > K then

% keep the remaining

for n = 1 to k “ K do

$$a_n(k) = a_n(k – 1) \tag{24}$$

end for

end if

4.2. Normalized Kernel Affine Projection Algorithm (NKAPA)

Normalization factor of APA is $G(k) = [U(k)^T U(k)+\varepsilon I]^{-1}$

For kernel APA it becomes

$$a_n(k) = a_n(k – 1) + \eta\, e(k, n)g(k) \tag{25}$$

5. EXPERIMENTAL RESULTS

In this section, we have a tendency to investigate the performance of the KAPA and APA algorithms for speech improvement at varied signal/noise ratios of various status. The step size used for each the APA and KAPA is 0.2. The separate noise corpus from NOIZEUS [9] were collected and extra to the clean Speech signals for the experimentation. At completely different uproarious levels, performances of those evaluated for speech improvement. Babble noise, Train noise, dissonance, automotive noise and building noise at 0, 5, 10, and 15 dB SNR were experimented. For this work, a complete of 20 datasets were generated.

The below figure 3 shows the first speech signal, APA and KAPA increased speech signals that area unit corrupted by automotive noise of 5dB SNR

The above figure 4 shows the Spectrograms of original speech signal, APA and KAPA improved speech signals that area unit corrupted by automotive noise of 5dB SNR.

6. PERFORMANCE ANALYSIS

The main objective of the adaptive filters is that the error signal e(k) reduction. Its success can clearly depends on the length of the adaptive filter, the character of the input signals, and also the adaptive algorithmic rule used. The signal is perceived by listeners reflects the subjective live of quality of speech signals. At 0 db the 2 signals are of equal strength and positive values are sometimes connected with higher comprehensibility wherever as negative values are connected with loss of comprehensibility because of

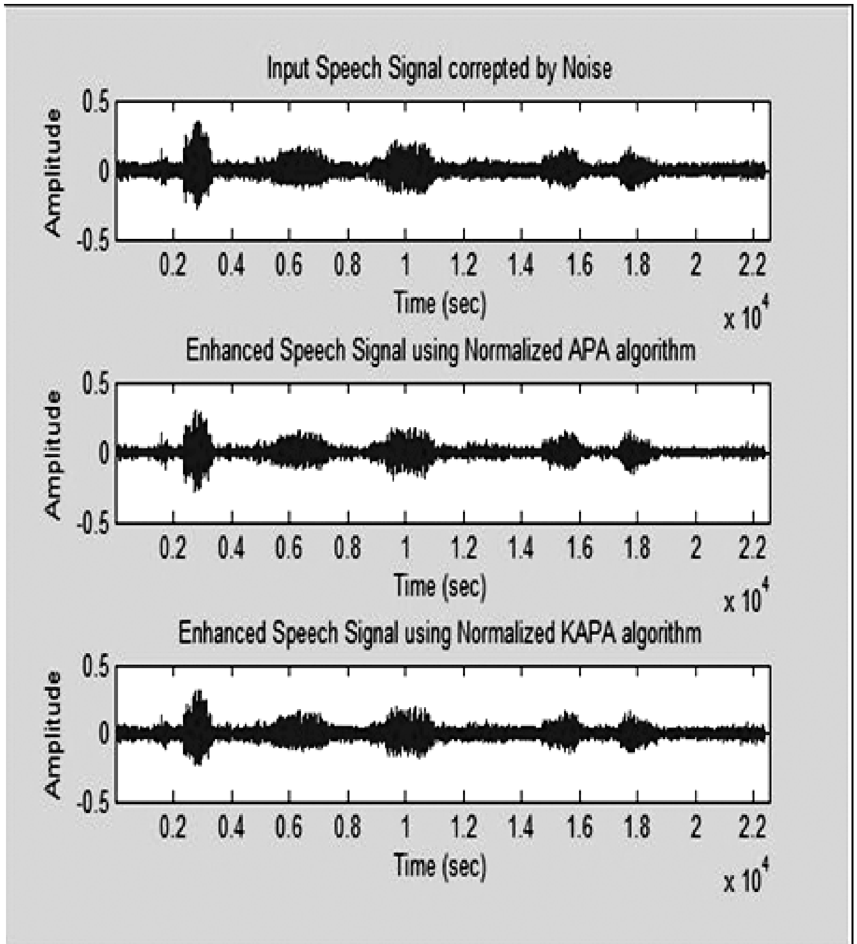

Figure 3: (a) Speech signal corrupted by automotive noise of 5 db (b) improved speech signal using NAPA (c) improved speech signal using NKAP Algorithm.

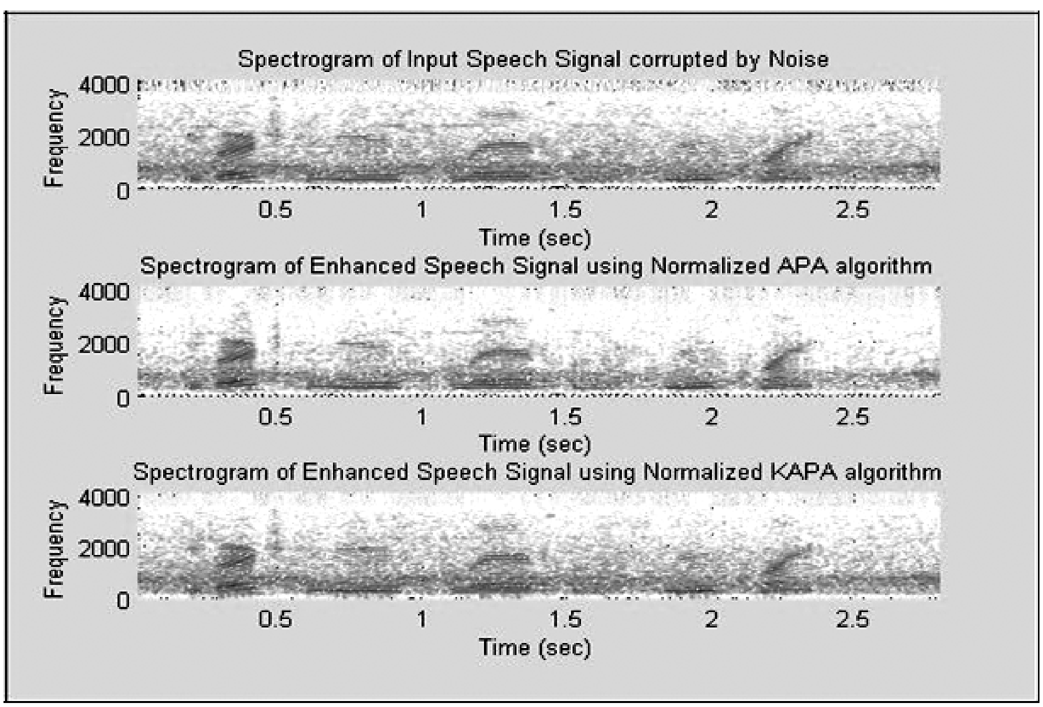

Figure 4: spectrograms of (a) Speech signal corrupted by automotive noise of 5 db (b) improved speech signal using NAPA (c) improved speech signal using NKAP Algorithm.

masking. Positive and better SNR values are found in all the algorithms. The performances are measured based on the metrics specifically MSE and SNR for all the algorithms.

6.1. Mean Square Error (MSE)

MSE is outlined as „mean of error squares " and is calculated victimization the formula

$$MSE = \frac{\sum (y_i - \hat{y}_i)}{n - p} \tag{26}$$

In order to quantify the distinction between values implied and also the true being calculable, the MSE of an estimator is employed.

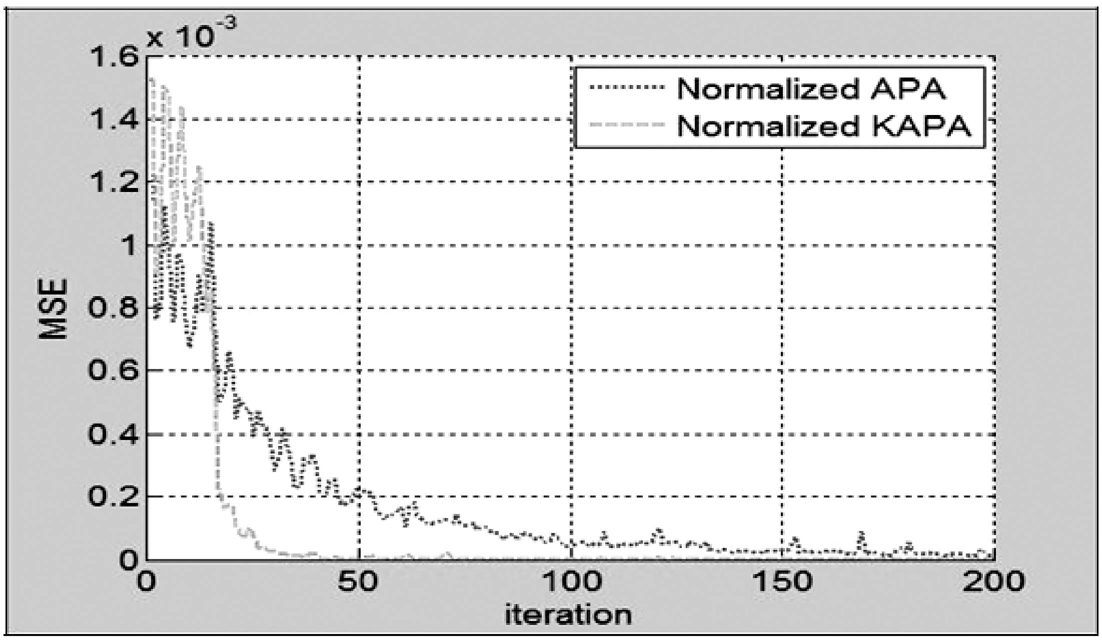

Figure 5: MSE (Learning Curves) comparison of Normalized „ APA and KAPA " algorithms for a Speech signal corrupted by Car Noise of 5dB

6.2. Signal to Noise Ratio (SNR)

Signal to Noise ratio (SNR) is outlined as the quantitative relation of power between the signal and also the unwanted noise. SNR is calculated victimization the formula

$$\frac{S}{N} = \frac{n_{signal}}{n_{ratio}} \tag{27}$$

One of the foremost vital goals of any speech improvement technique is to realize highest doable SNR. Higher the SNR ratios, higher the performance of speech signal sweetening. In given table one, we've shown the comparison of SNR values for the experimented algorithms APA and KAPA severally

7. CONCLUSIONS

The speech communication system performs greatly when the input signal has no limits or no noise effects and is degraded when there's a reasonably giant level of noise input signal. In such cases system cannot meet intelligibility, speech quality, or recognition rate needs. in this paper, a brand new methodology has been applied for speech improvement with RKHS. we tend to ascertained that there's a much better

Table 1
Comparison of SNR Values for APA and KAPA

Noise Type	*SNR (dB)*	*Enhancement Method*	
		APA	*KAPA*
Babble Noise	0	11.5697	23.6469
	5	6.2768	20.6057
	10	4.7025	18.1252
	15	-0.3462	12.4301
Train Noise	0	13.2165	23.1598
	5	12.7766	25.6758
	10	1.1339	15.1536
	15	-2.5412	11.5884
Car Noise	0	14.5846	24.7101
	5	9.2950	22.8052
	10	2.3719	16.3343
	15	-0.7025	12.4383
Restaurant Noise	0	10.2245	21.1858
	5	9.9622	23.9125
	10	0.0635	13.2941
	15	3.8029	16.2593

improvement in removal of ground noise in RKHS. The KAPA algorithmic rule has conjointly shown far better noise ratio values compared to the APA algorithmic rule.

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