Comparative Analysis of Different Speech Noise Cancellation Methods

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Abstract— Speech is the essence of life. Often the speech is corrupted with the undesired signal i.e. noise, thus concluding to the need of speech noise cancellation. It has gained huge attention in this modern world. Different methods such as adaptive filtering and wavelet thresholding for speech noise cancellation are compared and evaluated on their performance for noise cancellation in speech. Evaluation of various methods is done in terms of PSNR(Peak Signal to Noise Ratio), MSE(Mean Square Error), Correlation.

Keywords: - Speech noise cancellation, Adaptive filtering, Wavelet Transformation, MSE, PSNR, Correlation.

I. INTRODUCTION

Noise is non-informative and plays the role of sucking the intelligence of the original signal. Any kind of processing of the signal contributes to the noise addition. A signal traveling through the channel Speech noise cancellation is the most important field of speech enhancement. It is used for various applications such as mobile phones, teleconferencing, VoIP, etc. Reduction of noise from speech signals plays a vital role in modern communication systems. Adaptive filtering is a powerful technique for signal detection because of the random pattern of the noise and the non-deterministic sources of the interference. Wiener filters are a class of optimum linear filters which involve linear estimation of a desired signal sequence from another related sequence. Wavelet Transform is a mathematical approach for achieving and analyzing the signals both in frequency and time domain. Various algorithms such as LMS, NLMS, thresholding are derived for noise cancellation and comparison is made

II. METHODOLOGY

A. Adaptive Filtering

The principle of noise cancellation in this method is to obtain an estimate of the interfering signal and subtract it from the corrupted signal. Adaptive noise cancellation system [1]-[2], is basically a dual-input, closed loop adaptive control system as shown below, where x(n) is the input, d(n) is desired signal, e(n) is the error and y(n) is the filter output. For such structures the impulse response is equal to the filter coefficients. The coefficients for a filter of order p are defined as

$\mathbf{w}_n = [w_n(0), w_n(1), ..., w_n(p)]^T$ ....(1.1)

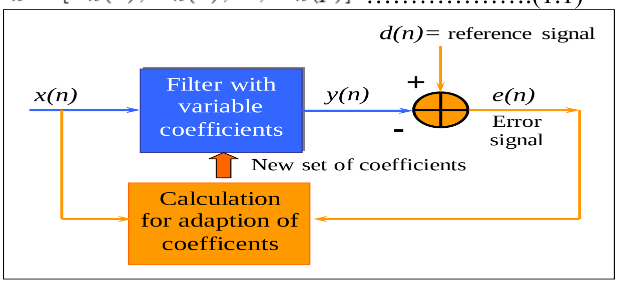

Fig. 1: Block diagram of an Adaptive Filter

The error signal or cost function is the difference between the desired and the estimated signal. The variable filter updates the filter coefficients at every time instant $\mathbf{w}_{n+1} = \mathbf{w}_n + \Delta\mathbf{w}_n$ where $\Delta\mathbf{w}_n$ is a correction factor for the filter coefficients. The adaptive algorithm generates this correction factor based on the input and error signals. LMS and NLMS define two different coefficient update algorithms.

B. Weiner Filter

Wiener filters are a special class of transversal FIR filters which build upon the mean square error cost function to arrive at an optimal filter tap weight vector which reduces the MSE signal to a minimum. The Wiener filter solves the signal estimation problem for stationary signals. [4].The Weiner filter is inadequate for dealing with situations in which non stationarity of the signal and/or noise is intrinsic to the problem In such situations, the optimum filter has to be assumed a time-varying form

Consider the output of the transversal FIR filter as given below, for a filter tap weight vector, **w**(n), and input vector, **x**(n).

$y(n)=\sum_{i=0}^{N-1} w(n)x(n-i)=w^T(n)\, x(n)$..................(2.1)

The mean square error cost function can be expressed in terms of the cross-correlation vector between the desired and input signals, **p**(n)=E[**x**(n) d(n)], and the autocorrelation matrix of the input signal, R(n)=E[x(n) x^T(n)].

$\xi(n)=E[e^2(n)]$......................................(2.2)
$=E[(d(n)-y(n))^2]=E[(d(n)-w^T(n)\,x(n))^2]$
$=E[d^2(n)-2d(n)\,w^T(n)\,x(n)+w^T(n)\,x(n)\,x^T(n)\,w(n)]$
$=E[d^2(n)]-2\,w^T(n)\,p(n)+w^T(n)\,R(n)\,w(n)$

The minimum value of ξ(n) can be found by calculating its gradient vector related to the filter tap weights and equating it to 0.

$\frac{\partial}{\partial wi} = 0$ for = 0,1,...,N

$\nabla = \left[\frac{\partial}{\partial w0}\ \frac{\partial}{\partial w1} \dots\dots\dots \frac{\partial}{\partial wN-1}\right]^T$

$\nabla\xi = 0$ ....(2.3)

By finding the gradient of equation (2), equating it to zero and rearranging gives us the optimal wiener solution for the filter tap weights, **w**o.

$\nabla\xi=0$
$2Rw_0-2p=0$
$w_0=R^{-1}p$ ....(2.4)

The optimal wiener solution is the set of filter tap weights which reduce the cost function to zero. This vector can be found as the product of the inverse of the input vector autocorrelation matrix and the cross correlation vector between the desired signal and the input vector

C. LMS(Least Mean Square) Algorithm

The *least-mean-square (LMS)* algorithm is a widely used algorithm. It is a type of adaptive filter known as stochastic gradient-based algorithms as it utilises the gradient vector of the filter tap weights to converge on the optimal wiener solution. This algorithm that consists of two basic processes: *A filtering process*, which involves computing the output of a transversal filter produced by a set of tap inputs, and generating an estimation error by comparing this output to a desired response. *An adaptive process*, which involves the automatic adjustment of the tap weights of the filter in accordance with the estimation error. Thus, the combination of these two processes working together constitutes a feedback loop around the LMS algorithm, as illustrated in the block diagram below:

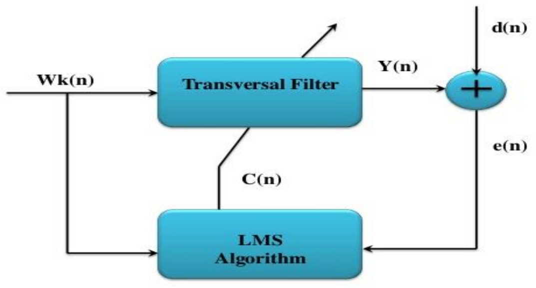

Fig. 2: Block diagram of LMS Algorithm

With each iteration of the LMS algorithm, the filter tap weights of the adaptive filter are updated according to the following formula

W(n+1)= W(n)+2μ e(n) x(n) ………………….(2.5)

The parameter μ is known as the step size parameter and is a small positive constant. This step size parameter controls the influence of the updating factor. Selection of a suitable value for μ is imperative to the performance of the LMS algorithm, if the value is too small the time the adaptive filter takes to converge on the optimal solution will be too long; if μ is too large the adaptive filter becomes unstable and its output diverges.

D. NLMS (Normalised Least Mean Square Algorithm)

One of the primary disadvantages of the LMS algorithm is having a fixed step size parameter for every iteration. This requires an understanding of the statistics of the input signal prior to commencing the adaptive filtering operation.[13] . In practice this is rarely achievable. Even if we assume the only signal to be input to the adaptive echo cancellation system is speech, there are still many factors such as signal input power and amplitude which will affect its performance. The normalised least mean square algorithm (NLMS) is an extension of the LMS algorithm which bypasses this issue by selecting a different step size value, μ(n), for each iteration of the algorithm.[15] This step size is proportional to the inverse of the total expected energy of the instantaneous values of the coefficients of the input vector **x**(n). This sum of the expected energies of the input samples is also equivalent to the dot product of the input vector with itself, and the trace of input vectors auto-correlation matrix, **R** .

$$\text{tr}[R] = \sum_{i=0}^{N-1} E[x^2(n-i)]$$
$$=E[\sum_{i=0}^{N-1} x^2(n-i)] \quad \text{……………………………(3.1)}$$

The recursion formula for the NLMS algorithm is

$$w(n+1)=w(n)+\frac{1}{x^T(n)x(n)}e(n)x(n).$$

The main drawback of the pure LMS algorithm is that it is sensitive to the scaling of its Input *x (n)*. This makes it very hard to choose a learning rate μ that guarantees stability of the algorithm .The normalized least mean squares filter (NLMS) is a variant of the LMS algorithm that solves this problem by normalizing with the power of the input.

E. (WT)Wavelet Thresholding

Methods discussed above analyse the speech signal in frequency domain only, whereas Wavelet transformation analyse the signal both in frequency and time domain. It also helps in multiresolution analysis.

De-noising using linear filters is not efficient for functions with discontinuities. This is due to the linear nature of this process, which prevents to efficiently estimate discontinuities. Wavelet approximation using thresholding allows an adaptive representation of signal discontinuities. We will thus use wavelet thresholding to perform a non-linear denoising.

Thresholding is done by the following definition:

$$d_{jk}^* = \begin{cases} d_{jk}, & |d_{jk}| \geq \lambda \\ 0\ , & |d_{jk}| < \lambda \end{cases}$$

where λ ≥ 0 is threshold value/parameter

It is of two types:

Soft Thresholding and *Hard Thresholding*. The hard thresholding method keeps some coefficients fixed and sets others to 0; in contrast the soft thresholding method either ‘shrinks’ or sets them to 0.The noisy signal is basically of the following form:

s(n) = f(n) +σ e(n)

where time n is equally spaced. In the simplest model, suppose that *e*(*n*) is a Gaussian white noise *N*(0,1) and the noise level σ is supposed to be equal to1. The de-noising objective is to suppress the noise part of the signal *s* and to recover *f*. The de-noising procedure proceeds in three steps:

1) Decomposition. Choose a wavelet, and choose a level N. Compute the wavelet decomposition of the signal s at level N.

2) *Detail coefficients thresholding*. For each level from 1 to N, select a threshold and apply soft thresholding to the detail coefficients.

3) *Reconstruction.* Compute wavelet reconstruction based on the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N.

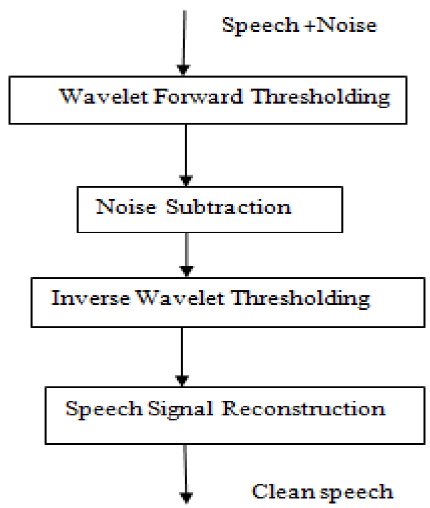

Fig. 3: Block diagram of wavelet thresholding

III. EXPERIMENTAL SETUP

We have implemented adaptive filters inMATLAB version R2010a. To generate wavelet transform, 'haar' wavelet family is used.

For adaptive filtering, predefined function 'adaptfilt' in MATLAB is used. It creates adaptive object based on algorithm used (e.g.adaptfilt.lms/adaptfilt.nlms).

To observe the performance of different methods of noise cancellation over speech, sinusoidal signal and sound file (in wav format) are processed.

A GUI(Graphical User Interface) is also created to provide better interface for the user. By simply clicking on different buttons of GUI results are obtained.

IV. RESULTS

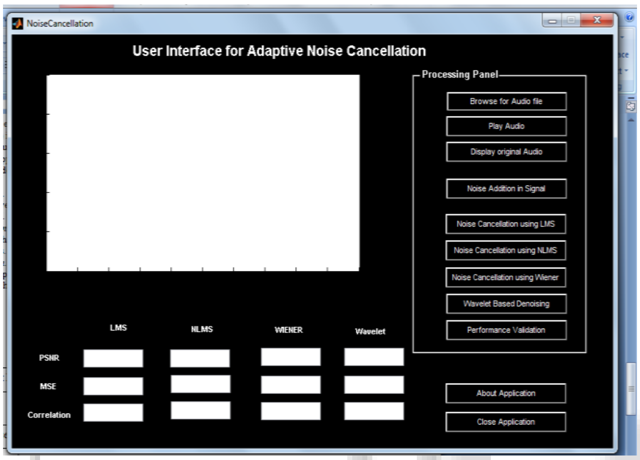

Fig. 4: Graphical User Interface

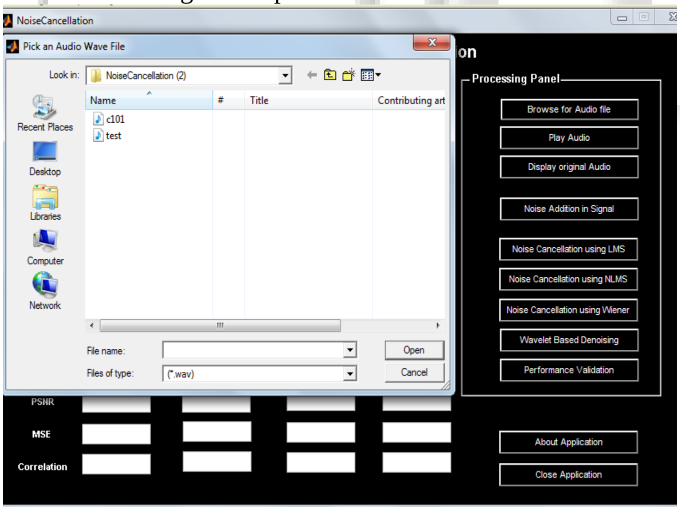

Fig. 5: Browsing an audio file

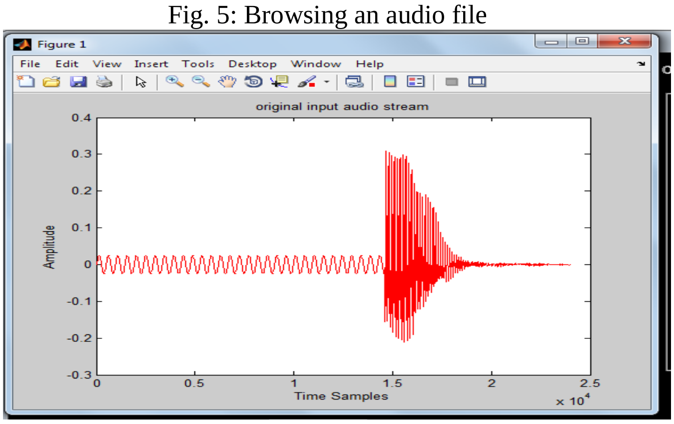

Fig. 6:Displaying an audio signal

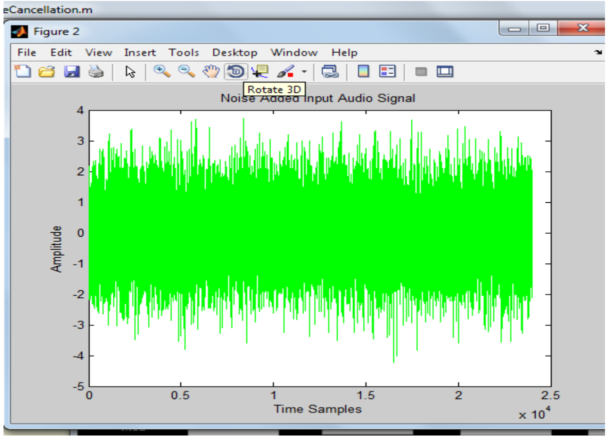

Fig. 7: Noise added speech

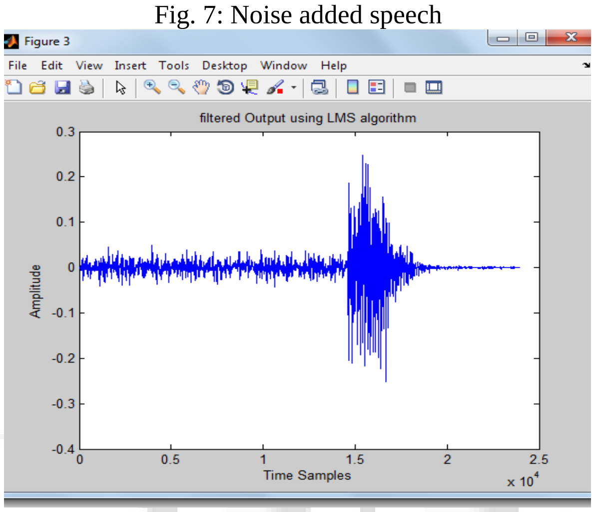

Fig. 8: Filtered output using LMS algorithm

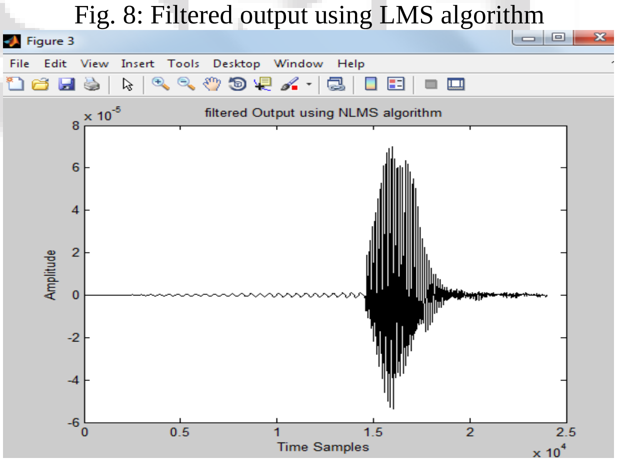

Fig. 9: Filtered output speech using NLMS algorithm

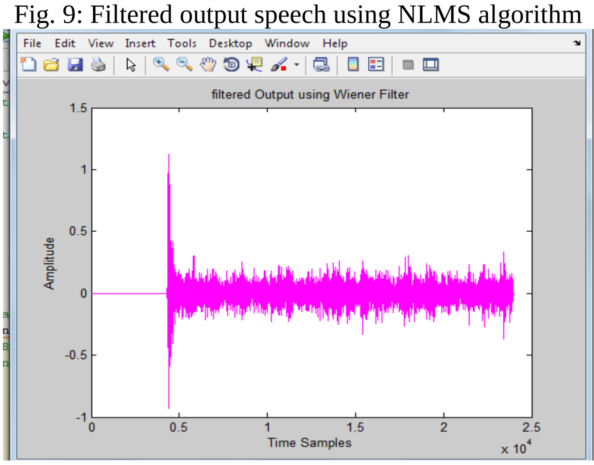

Fig. 10: Filtered output using Weiner Filter

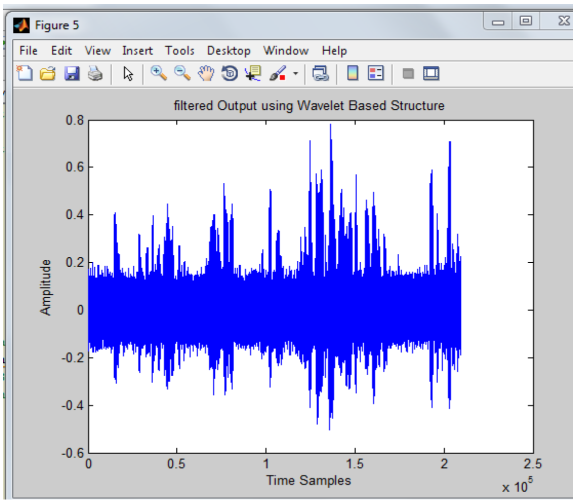

Fig. 11: Filtered output using Weiner Filter

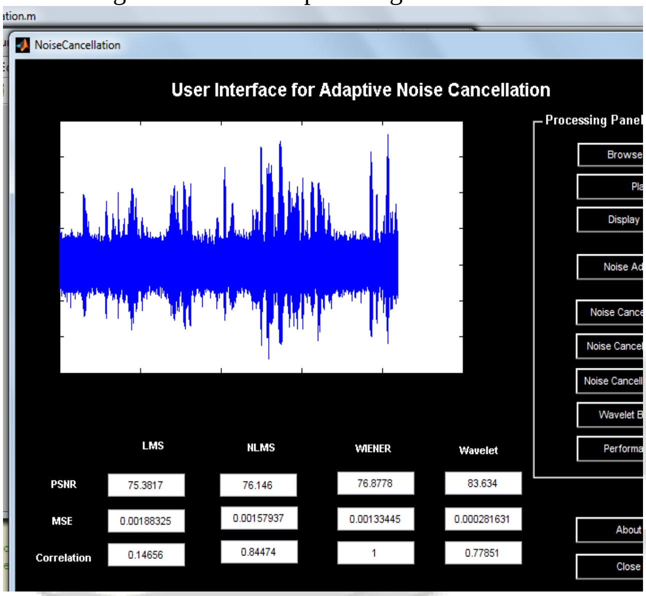

Fig. 12: Performance Validation of all methods discussed.

TABLE. 1: Performance Evaluation of different methods

	LMS	NLMS	WEINER	WAVELET
PSNR	75.381	76.146	76.8778	83.634
MSE	0.0018	0.0015	0.0013	0.0002
CORRELATION	0.146	0.146	1	0.7789

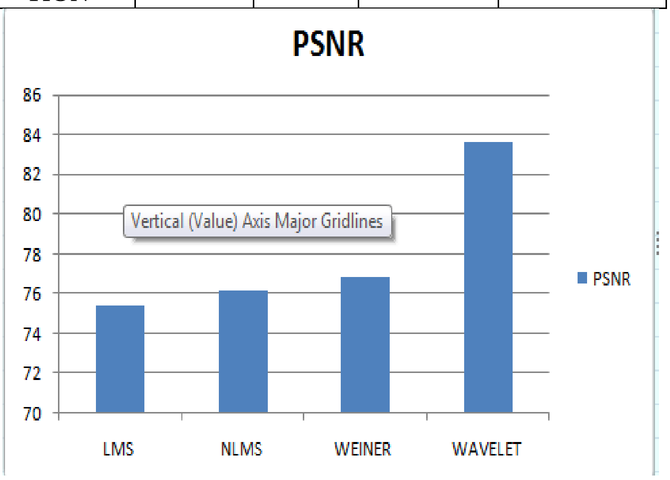

Fig. 11: Graphical Representation of PSNR for various methods

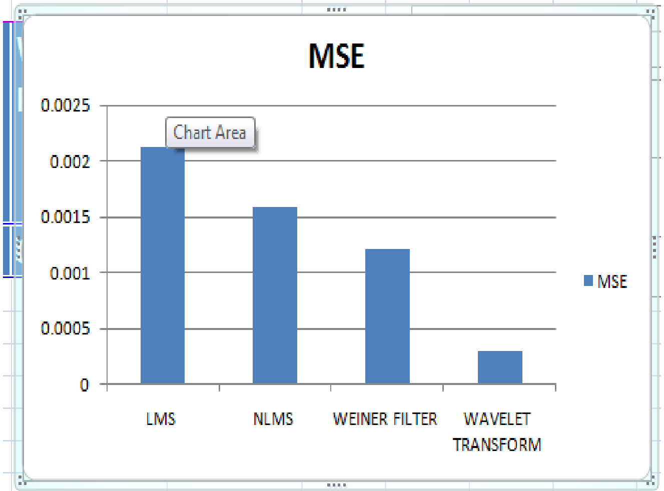

Fig. 12: Graphical Representation of MSE for various Methods

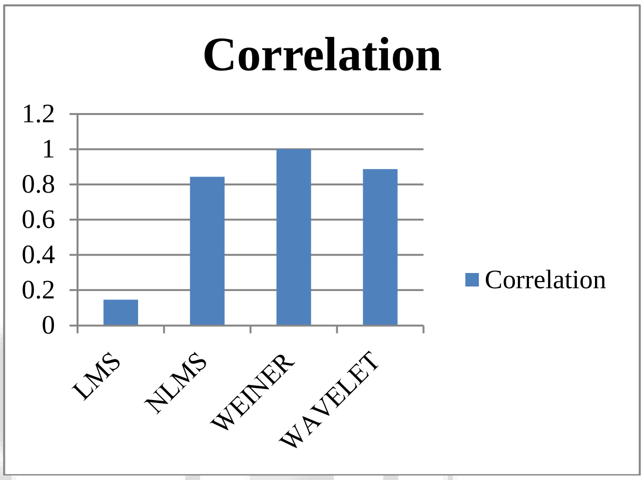

Fig. 13: Graphical Representation of CORRELATION for various methods

V. CONCLUSION

As shown in above screen shots and graphs among the outputs of three algorithm: LMS, NLMS and Threshold, most reliable algorithm is thresholding. Among the adaptive filters: LMS and NLMS, as shown in output that performance of NLMS algorithm is improved than LMS algorithm, however, it costs in the form of increased computational complexity.

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