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SPEECH ENHANCEMENT USING A TWO-STAGE ADAPTIVE NOISE CANCELLER

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ABSTRACT

The problem of recognizing speech under noisy conditions is an as-yet-unsolved problem.

The continual evolution of these methods and the composite of multiple methods working together will undoubtedly provide better systems in the future. The present paper deals with an important and up to date subject, namely, adaptive filter and its application used in speech recognition in the presence of acoustic background noise.

This paper presents the proposed TSANC (Two Stage Adaptive Noise Canceller). It improves the trade-off between convergence speed and steady state performance. Such a noise canceller is a cascade of two adaptive noise cancellers; a short noise canceller and another long one. The first one is much better to be a short, for being rapid, but this leads to coarse convergence and will not enable high quality to the recovery processed speech signal. The second noise canceller is long; and it ensures refinement of noise cancellation whose adaptation soon starts after the convergence of the short one. Due to the partial noise cancellation offered by the last one, both the convergence time and steady state error of the long noise canceller will be considerably reduced, and the length of the long noise canceller is determined by the desired precision of noise cancellation.

Keywords: *speech recognition, adaptive filter, noise canceller*

الملخص

على الرغم من الطرق العديدة التى اقترحت لتحسين أنظمة تمييز الأصوات فإن مشكلة التعرف على الأصوات في ظروف الضوضاء الشديدة لم تجد حلا" بعد.

يتعامل هذا البحث مع مادة علمية هامة و متزامنة مع احتياجات الوقت الحالي تحت مسمى المرشحات المتكيفة وتطبيقاتها المستخدمة في التعرف على الأصوات في وجود الضوضاء الصوتية الصاخبة. ولقد تم طرح طريقة لتحسين مستوى أداء التعرف على الأصوات وذلك عن طريق تطوير المرشحات المتكيفة لإزالة الضوضاء. وهذا التحسين يكمن في زيادة سرعة التقارب و تقليل درجة ثبات الخطأ لخوار زم الموائمة وإعطاء تتبع سريع في الأجواء المتغيرة. إن مثل هذا المرشح المذكور يحتوى على تصميم بسيط ، حيث أنه يستخدم أسلوب مرشح رد الاندفاع المحدود تحت مسمى المرشحات المتكيفة ثنائية المراحل وهذه المرشحات المتكيفة الثنائية المراحل سريعة التتبع. ولقد تم استخدام خوار زم

اقل المتوسطات المربعة في المرشحات المتكيفة ذات رد الاندفاع غير المحدود في أول مرحلة مـن الحلـول البديلـة وكانت النتائج غير كافية وقد تم الحصول على نتائج ممتازة من المرشح المتكيف ذا رد الاندفاع غير المحدود باستخدام خوار زم متغير الوسيط التفاضلي، حيث أن هذا المرشح يتمتع بمعدل تقـارب ممتـاز و تصـميم مـرن. وتسـتخدم المقترحات السابقة لتحسين مستوى الأداء في تمييز الأصوات تحت تأثير الضوضاء و ذلك بزيادة قيمة إزالة الضوضاء للحصول على أعلى كفاءة للإشارات الصوتية المعالجة. و لقد تم استخدام الأساليب الرياضية و أساليب المحاكاة علـى الحاسب الشخصي لاختبار معدل ثبات مستوى أداء الخوارزميات و الأساليب سابقة الذكر وكذلك تم قياس معدل أدائهـا ومقارنتها بالأساليب التقليدية .

1. INTRODUCTION

A common feature of using the previous adaptive noise canceller **ANC** in speech signal by **LMS** (Least Mean Square) needs a relatively long time to converge to the optimum setting. This drawback may not be tolerable in case of rapid change of the noise level under the environmental conditions. Besides, the lost segment of the speech signal during this time may be great. The proposed **TSANC** is presented in order to improve the trade-off between convergence speed and steady state performance. This noise canceller is a cascade of two adaptive noise cancellers, a short noise canceller and a long one. The first noise canceller much better be a short one as it has rapid, but coarse convergence and will not enable high quality to the recovery processed speech signal. The second noise canceller is long to ensure refinement of the noise cancellation whose adaptation is to start after the convergence of the short one. Due to the partial noise cancellation offered by this latter, both the convergence time and the steady state error of the long noise canceller will be considerably reduced, and the length of the long noise canceller is determined by the desired precision of noise cancellation [Boll, 1979] and [Barnwell, 1996].

The present paper is organized as follows: section 2 gives idea, scheme, and theoretical analysis of the proposed **TSANC**]. Computer simulation of the proposed scheme are given in section 3 along with a comparison with the conventional ones [Sondhi, 1981] and [Martins, 1993].

2. PROPOSED TSANC SCHEME

The proposed adaptive noise-canceling scheme is shown in Fig.1. It consists of two transversal filters F_1 and F_2. The first filter has a small number of tap-weights, say L_1, while the second has a greater number of tap-weights, say L_2. The principle of operation of this scheme relies on the following two factors, which are to be discussed on. The first one is the fact that as the noise canceller length, L, increases; adaptive noise canceller becomes more precise. This is due to the fact that at large values of L, the noise canceller approximates well. Consequently, the inverse filter for the noise is to be canceled. Also, the value of step size μ, which ensures the stability of the adaptive process; is related to L via the relation

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$$0 < \mu < 2/(L\ P_{inp}) \tag{1}$$

where $P_{inp} = E(\hat{N}_k^2)$ is the power of noise canceller input. It is clear that as L increases the allowable μ decreases and consequently, the convergence speed decreases. From this discussion, the choice of L is a trade-off between the speed of convergence and the noise canceller precision.

Now, the dependence of the noise canceller performance, given by the convergence time and the residual mean square error, on the step size μ and noise canceller length is to be discussed. As the noisy speech signal x (k) is equivalent to both the sending speech signal S(k) and the additive noise $N_1(k)$. The following model in case of the sending speech signal is absent is to be used, i.e. S(k)=0

$$x(k) = N_1(k) = \hat{w}_{opt}^T \hat{N}_k \ + \ e'_k \tag{2}$$

where $\hat{W}_{opt}$ is the coefficient vector of the filter with L coefficients that is closest to the exact noise in the noisy speech signal path that is derived from a sensor called the primary sensor.

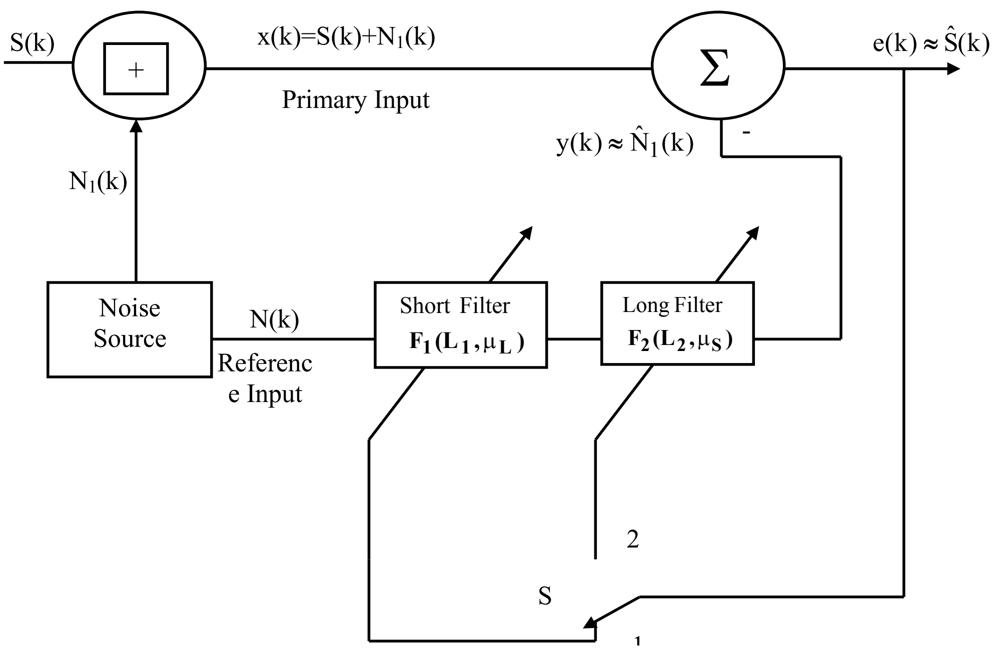

Fig. 1 The proposed TSANC scheme

e'_k is due to fact that the exact additive noise requires a filter having, usually, an infinite number of coefficients. The level of this error increases as L decreases. The weights are adapted in the learning mode, **LM**; according to the algorithm in the following equation,

$$\hat{w}_{k+1} - \hat{w}_k = \mu(x(k) - y(k))\hat{N}_k \tag{3}$$

where $\hat{\mathbf{w}}_{\mathbf{k}}$ and $\hat{\mathbf{N}}_{\mathbf{k}}$ denote the column vectors of the tap-weights and the input noise signal samples at the k^{th} iteration for a noise canceller with length L and step size μ , i.e;

$$\hat{w}_k = [w_k(0), w_k(1), \ldots\ldots\ldots, w_k(L-1)]$$

and

$$\hat{N}_k = [N(k), N(k-1), N(k-2), \ldots\ldots\ldots\ldots, N(k-L+1)] \tag{4}$$

Substitute Eq. (2) in Eq. (3), leads Eq. (4) to become

$$\begin{aligned}
\hat{w}_{k+1} - \hat{w}_k &= \mu\ ((N_1(k)) - \hat{w}_k^T \hat{N}_k)\hat{N}_k \\
&= \mu\ ((\hat{w}_{opt}^T \hat{N}_k + e'_k) - \hat{w}_k^T \hat{N}_k)\hat{N}_k \\
&= \mu\ (e'_k \hat{N}_k + (\hat{w}_{opt} - \hat{w}_k)^T)\hat{N}_k \hat{N}_k \\
&= \mu\ \ e'_k \hat{N}_k + \mu\ (\hat{w}_{opt} - \hat{w}_k)^T\ \hat{N}_k \hat{N}_k \\
&= \quad T_1 \quad + \quad T_2
\end{aligned} \tag{5}$$

When convergence occurs $\hat{w}_k$ becomes close to $\hat{w}_{opt}$ and then term T_2 vanishes. The weight fluctuations in Eq. (4) are then mainly due to the term T_1, which can be reduced by increasing the noise canceller length (in order to reduce e'_k as mentioned above) and/ or decreasing the step size. This operation is achieved by using two-cascaded filter whose adaptation process contains two stages. In the first stage, the short filter is to start the adaptation process while the long one is to terminate and is used as an identity filter whose central coefficient is set to unity while the remaining ones are set to zero.

The weights of the short filter are adapted in this stage according to the algorithm that is described above in Eq. (5). μ_L is defined as the large step size and L_1 is a small number of coefficients that are used to increase the convergence speed. When the convergence occurs, the weight fluctuation is mainly due to the term T_1 while the term T_2 is to vanish as mentioned above. To decrease the fluctuations that are related to the steady state error, in order to give a high quality of the processed speech signal against the noise cancellation; it requires changing the step size μ_S to a smaller value than the defined μ_L and the length of the filter (L_2) is to be larger than the defined L_1. Transfer the mode of adaptation from the first stage to the second stage can achieve this. This stage uses the long filter with length L_2 and step size μ_s to start in adaptation while the short one is to terminate and keep with its optimum coefficients. The first moment at which the mode of adaptation is to transfer from the first stage to the second stage, where the initial setting of long filter coefficients is an identity and the short filter coefficients become an optimum is described as,

$$\hat{w}_{k+1} - \hat{w}_k = \mu_S((N_1(k)) - \{\hat{w}_{opt}^T \hat{N}_k\}\ \{I\})\hat{N}_k \tag{6}$$

Substitute Eq. (2) in Eq. (6) leads to;

$$\begin{aligned} \hat{w}_{k+1} - \hat{w}_k &= \mu_S((\hat{w}_{opt}^T \hat{N}_k + e'_k) - \{\hat{w}_{opt}^T \hat{N}_k\}\ \{I\})\hat{N}_k \\ &= \mu_S(e'_k)\hat{N}_k \qquad (7) \\ &= T'_1 \end{aligned}$$

From Eq (6), it can be noticed that the weight fluctuations in the second stage has decreased due to $T'_1 < T_1$, this decreases, in accordance; the residual mean square error, and the updating coefficients of the long filter after this moment become near to their optimum value.

The second factor on which relies the idea of the proposed **TSANC** is the fact that the greater the deviation of the initial setting of the noise canceller from its optimum setting is, the greater will be the convergence time. This fact can be justified as follows. For simplicity we shall assume the additive noise is equivalent to the optimum noise canceller, i.e.;

$$N_1(k) = \hat{w}_{opt}\ \hat{N}_K^T \tag{8}$$

In this case, the adaptation algorithm that operates in the learning mode, is given by,

$$\begin{aligned} \hat{w}_{k+1} &= \hat{w}_k + \mu(\hat{w}_{opt}^T \hat{N}_k - \hat{w}_k^T \hat{N}_k)\ \hat{N}_k \\ &= \hat{w}_k - \mu \hat{N}_k\ \hat{N}_k^T\ (\hat{w}_k - \hat{w}_{opt}) \end{aligned} \tag{9}$$

Let $\dot{M}$ be an integer ,such that the sequence $\hat{N}_k \hat{N}_k^T$ exhibits the periodicity over $\dot{M}$ baud interval ,thus

$$\sum_{j=k}^{k+\dot{M}-1} \hat{N}_j N_j^T = \dot{M}\,R \tag{10}$$

In practice $\dot{M}$ are usually few tens .One has

$$\begin{aligned} \hat{w}_{k+\dot{M}} &= \hat{w}_k - \mu \sum_{j=k}^{k+\dot{M}-1} \hat{N}_j \hat{N}_j^T (\hat{w}_j - \hat{w}_{opt}) \\ &= \hat{w}_k - \mu \left\{ \sum_{j=k}^{k+\dot{M}-1} \hat{N}_j \hat{N}_j^T \right\} \{(\hat{w}_k - \hat{w}_{opt}) + (\hat{w}_j - \hat{w}_k)\} \end{aligned} \tag{11}$$

When μ is small $\hat{w}_j - \hat{w}_k, k \le j \le k + \dot{M} - 1$ will be small with respect to $\hat{w}_k - \hat{w}_{opt}$ (especially at the start of adaptation). Then

$$\begin{aligned} \hat{w}_{k+\dot{M}} &= \hat{w}_k - \mu \sum_{j=k}^{k+\dot{M}-1} \hat{N}_j \hat{N}_j^T (\hat{w}_k - \hat{w}_{opt}) \\ &= \hat{w}_k - \mu\, \dot{M} R (\hat{w}_k - \hat{w}_{opt}) \end{aligned} \tag{12}$$

Subtracting $\hat{w}_{opt}$ from both sides, and denoting $v_k = \hat{w}_k - \hat{w}_{opt}$ then Eq. (12) becomes

$$v_{k+\dot{M}} = (I - \mu \dot{M} R)\, v_k \tag{13}$$

From this equation one can obtain

$$v_{n\dot{M}} = (I - \mu \dot{M} R)^n\, v_0 \tag{14}$$

where v_0 is the deviation of the initial setting from the optimum .To attain a given precision of noise cancellation, prescribed by value of $|V_{n\dot{M}}|$; the value of n increases with the increase of $|V_0|$ .Consequently; the convergence time of the noise canceller is an increasing function of its initial shift from the optimality.

The idea of the proposed **TSANC** is based on the above two facts, the noise canceller F_1 has small number of coefficients L_1. So, the allowable step size, μ_L, is large. This enables the use of a large value of μ_L and then F_1 converges rapidly. The partial adaptive noise canceling offered by this noise canceller makes the distortion in the speech signal in front of F_2, while the cascade of F_1 is a mild one. This reduces the steady state error at the output of the long noise canceller. It also reduces the deviation between the initial setting of this noise canceller and the optimal one and then the convergence time is decreased [Shawky, 2001].

The theory of operation of the adaptation of the proposed noise canceller is as follows:

At the start of adaptation process, only the coefficients of the short noise canceller are updated, after the convergence of the short noise canceller has been settled, say after k_S samples, the adaptation of the long noise canceller is started while the adaptation of the short one is terminated. The reason for this termination is to protect the long noise canceller from the adaptation noise.

There are two methods of switching between the short and long noise canceller. In the first method k_s is taken as a fixed number of iterations that is equal to the maximum expected convergence time of the short noise canceller. In the second one, k_s, is adaptive. The latter method optimizes the value of k_S, however, it is more complex than the first method since the convergence time of the short noise canceller is a small portion of the total convergence time of the adaptive noise canceling scheme, then optimization of k_S is not worth doing. Hence, the first method is preferred.

Now, estimation of maximum value of the convergence time of the short noise canceller is done as follows: in the **LMS** algorithm, the largest time constant corresponds to the minimum eigen value, which is given by

$$\tau_{max} = (1/(2\mu_L \lambda_{min}) \tag{15}$$

Relation between the time constant and the convergence time is usually given by

$$Tc_{max} = 3\tau_{max} \tag{16}$$

Form Eqs. (6 and 7), the maximum value of k_S, denoted by k_{Smax}, is given by

$$k_{Smax} \equiv Tc_{max} = 3/(2\mu_L \lambda_{min}) \tag{17}$$

A round figure of k_{Smax} can be obtained by doing the approximation, $\lambda \min \approx E(N_k^2)$ which lead to $k_{Smax} \approx 3/(2\mu_L E(N_k^2))$. To compensate for the previous approximations, the designer can use a value greater than twice the value $3/(2\mu_L E(N_k^2))$ i.e.

$$k_{S\max} = 3/(\mu_L E(\hat{N}_k^2)) \tag{18}$$

The number of multiplication per iteration of the proposed **TSANC** is computed as follows. At start of adaptation F1 is only adaptive, so the number of multiplication is $2L_1$ during adaptation of F_2, This happens when adaptation of F_1 is stopped. Thus, the number of multiplication is $2L_2+L_1$: L_1 for F_1 and $2L_2$ for F_2. Thus; the maximum number of multiplication per iteration is L_1+2L_2.

To reach the precision of the proposed **TSANC** by a conventional one-filter noise canceller, the noise canceller length L will be greater than L_2. Then the number of multiplication in the proposed **TSANC** and the conventional one is given by

$$r' = (2L_2+L_1)/(2L) \tag{19}$$

The value of r' is close to one, since $L_1<L_2$ and $L_2<L$. then the proposed **TSANC** does not require more computing power than the conventional one if the two schemes are to have the same precision [Barnwell, 1996] and [Martins, 1999].

3. COMPUTER SIMULATION

This section concerns with the simulation of the **TSANC** whose construction is given in Fig. 1. We have represented the voiced speech waveform for males as shown in Fig. 3-a. This speech signal, which was recorded using the computer for 10 sec; has the following properties: 8 kHz sampling rate, 16 bit used (16 bit **A/D** sound card), and the coding is with **PCM**. The acoustical additive noise will be considered with zero mean white noise. The distorted (noisy) speech signal, which is as shown in Fig. (3-b); can be realized by considering the generated white noise be applied to the recorded speech signal. We have considered that the level of the white noise power is higher than the power of the clear (pure) voiced speech signal. As a result, this pure speech signal is to be distorted to reach with its **SNR** over the defined period (10 sec) to a level of –12.95 dB. This **SNR** is enough to make listening the signal too difficult. The adaptive noise canceller (**ANC**) in our simulation can be realized by using a transversal filter and the measuring results is evaluated by plotting $\bar{\varepsilon}_k$ which is defined as the normalized sum square error (**NSSE)** versus iteration number k. From this evaluation, convergence time, steady state error performance, and the quality of speech enhancement are obtained. The undesired white noise can be reduced by one of the following methods. The first one is the conventional **ANC,** which is to be realized when using a transversal filter and the **LMS** algorithm that update the coefficients, such that length L=10 and the associated step size is μ =. 0001. Repeating the adaptation process using filter with smaller length L=5 and with larger step size μ =. 001.

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While the second method proposes an adaptive noise canceller (**TSANC**), which is to be realized by using two transversal filters (short and long **ANCs**) and the coefficients of both of them are to be updated according to the **LMS** algorithm. At the start of adaptation process, each one of the two noise cancellers is an identity filter (the central coefficient is set to unity while the remaining ones are set to zeros). The proposed **ANC** lengths are L_1=5 and L_2=10, the associated step sizes are μ_L = 0. 001 and μ_S=. 0001. The value of T_C, as calculated from Eq. (8), is 5800 iterations.

The **NSSE** of the proposed and conventional **ANC**s are shown in Fig. 2. In this figure, curves "LMS L=10 step size=0.0001" and correspond to the conventional **ANC** with higher order length, smaller step size, while "LMS L=5 step size=0.001" with lower order length, larger step size correspond to the proposed **ANC**. The measured values of the first curve with no adaptation are related to right **NSSE** axis while the other curves are related to the left axis. The two curves are mainly evaluated to display the effect of changing the setting length and the step size on the performance of the conventional **ANC**. From these two curves, the following Table 1 can be obtained.

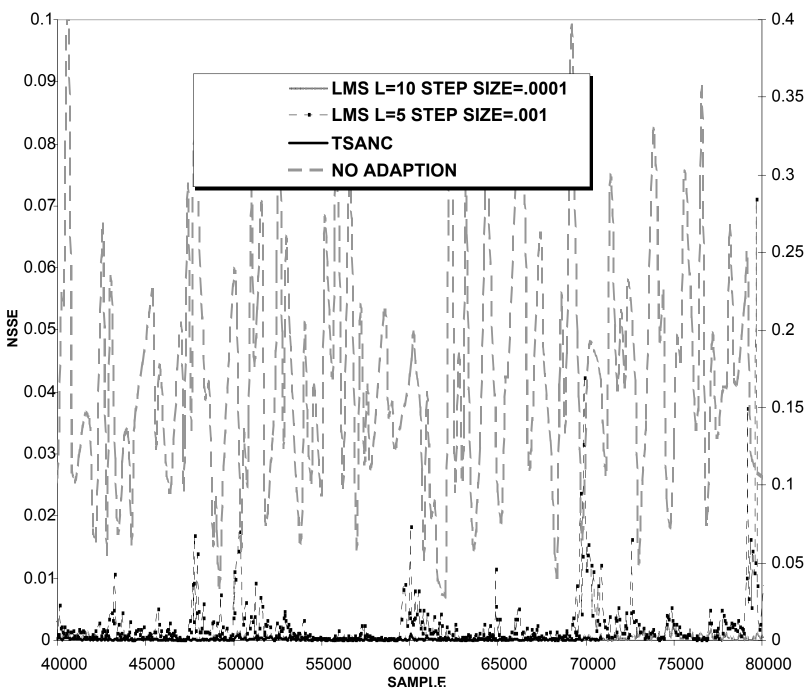

Fig. 2 Comparison between LMS and TSANC algorithm using the SNR of the noisy speech signal = - 12.9 dB for sample from 0 to 40000

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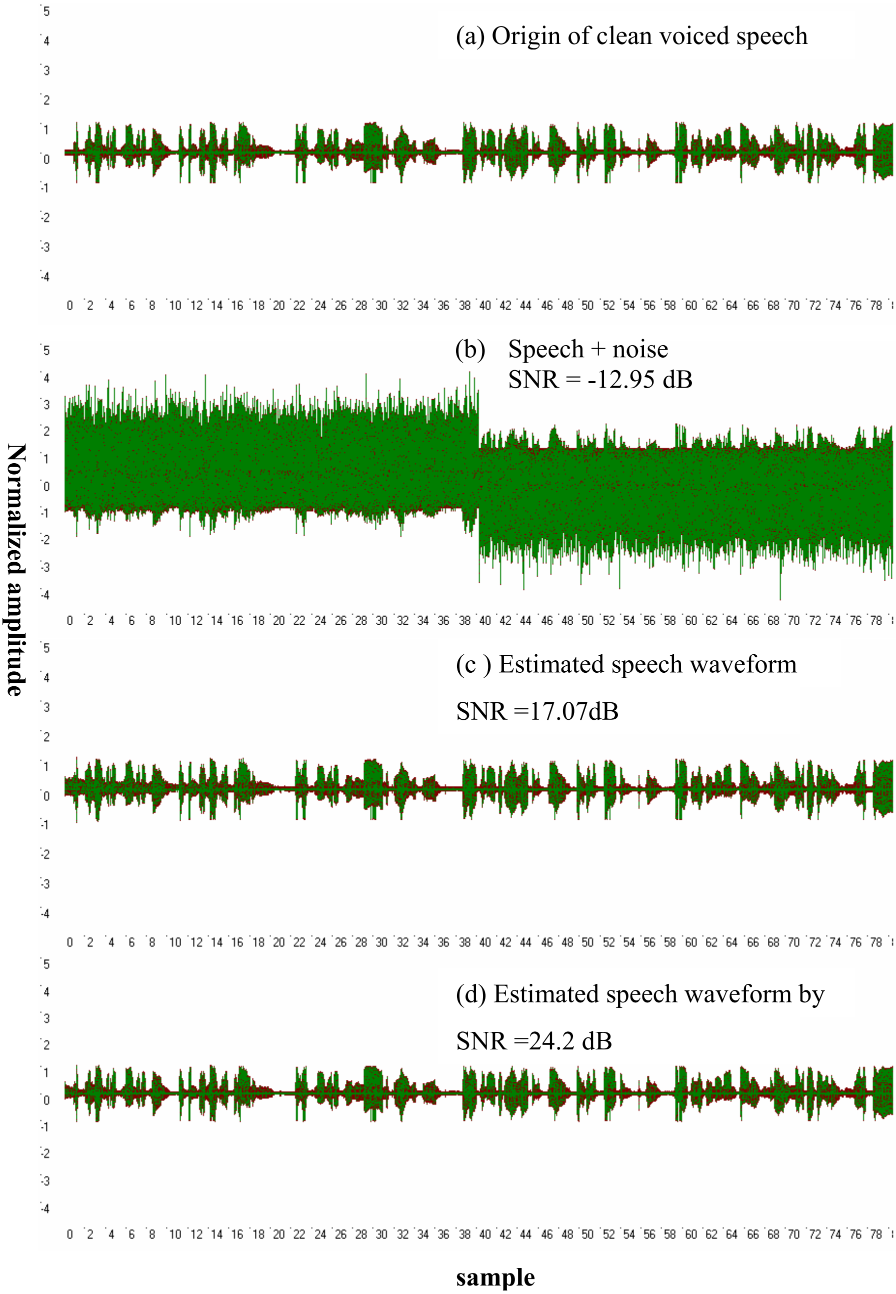

Fig. 3 The difference between estimated speech waveform of LMS and TSANC algorithm, using sampling rate of 8 kHz and SNR of noisy speech signal =-12.9 dB.

Table 1. Performance of **LMS** algorithm for variable length, step size, using a speech signal with SNR= -12.95 dB

Filter order Step size	L=10 μ =0.0001	L=5 μ =0.001
Convergence time	27000	5000
Steady state error	LOW	HIGH
The quality of speech enhancement (SNR in dB)	17.07 dB	22.95 dB

From Table.1, it should be mentioned that both the convergence speed and the steady state error depend on the step size and length of **ANC**. Consequently, decreasing the step size and increasing the order of the filter lead to an increase in the convergence time and a decrease in the steady state error (fluctuation). From curve "TSANC" of the proposed **ANC**, the following notes stem up:

(1) The convergence time decreased and was approximately equal to the decreased convergence time of conventional **ANC** whose length =5 and step size =0. 001, which corresponds to curve" LMS L=5 step size = 0.001"

(2) The steady state error also decreased and approximately equal to the decreased steady state error of the conventional **ANC** whose length =10 and step size =0.0001that corresponding to curve" LMS L=10 step size = 0.0001".

Thus, the proposed **TSANC** not only has led to faster convergence but also has led to better steady state performance than the conventional **ANC** [Martins, 1999].

During the adaptation process, the output of the **ANC** is subtracted from the presented noisy speech signal; gives an estimated value of the clean speech signal (e (k)). Another comparison between the performance of the **ANC**s is obtained by plotting the estimated speech signal value (e (k)) versus iteration No. k, and the **SNR** is evaluated for the corresponding estimated speech signal to measure the quality and the amount of noise reduction in our simulation. The normalized amplitude of the estimated speech signal versus k of the conventional adaptive noise canceller is shown in Fig. 3-c and that of the proposed **TSANC** is shown in Fig. 3-d. The **SNR** of the estimated speech waveform is evaluated for both the conventional **ANC** and the proposed **TSANC**, giving the values 17.07dB and 24.2dB respectively. It is clear from Figs. 3-c and d and from the measuring values of the **SNR**; the quality of the processed speech signal by the proposed **TSANC** is higher than the conventional one. Thus, the amount of noise reduction achieved by **TSANC** is higher than the conventional **ANC**.

To measure the performance of the proposed **TSANC** in another case of decreasing the additive noise power, the same procedure explained in the previous case will be followed. The representation of the voiced speech waveform will be displayed again in Fig. 5-a, to be considered as, the clean speech signal. Consider an acoustic additive white noise with lower power than the previous case is appended to the voiced speech waveform. By this way we have been obtained a noisy speech signal with a **SNR** of -3.93 dB as shown in Fig.(5-b). The conventional **ANC** is realized by choosing the filter with length L=10 and the step size μ=0.0001, and is realized again by setting another values of a filter with length L=5 and the step size μ=.001,while the proposed **TSANC** is realized and the two cascade **ANC**s lengths are L_1=5 and L_2=10 coefficients. The values of L_1 and L_2 are chosen to give the required precision, as mentioned above. For μ_L =0.001 and μ_S=0.0001, the **NSSE** versus k is given in Fig. 4, respectively; T_C = 5400 , from Eq. (8) and Fig. 4, curves "LMS L=10 step size=0.0001","LMS L=5 step size =0.001" show the evolution of **NSSE** in the case of conventional schemes while curves "TSANC" represent the proposed schemes. These curves show that in case of the conventional **ANC**, the following results, presented in Table 2; are obtained.

Table.2 Performance of **LMS** algorithm for variable length, step size, using a speech signal with **SNR** =-3.93 dB.

Filter order Step size	L=10 μ =0.0001	L=5 μ =0.001
Convergence time	45000	5500
Steady state error	LOW	HIGH
The quality of speech enhancement(SNR in dB)	1.3 dB	11.1 dB

From Table.2, when L=10 and step size=0.0001; the convergence time increases more than the previous case of Fig. 2 due to the decrease of the additive noise level. Also, to obtain smaller steady state error the convergence time should be increased as shown in curve "LMS L=10 step size=0.0001". While, obtaining the high speed convergence by decreasing the length filter and increasing the step size value as shown in curves "LMS L=5 step size=0.001", giving an increasing in the steady state error.

In case of the proposed **ANC**, we obtain the following results. The proposed **TSANC** not only has smaller convergence time but also has smaller residual mean square error than the conventional **ANC**. The other method, to test the performance of the **ANC**s is evaluated by plotting the estimated speech signal (e(k)) value versus k and also by calculating the **SNR** values to each estimated speech signal. Fig. 5-c shows the estimated speech waveform by the conventional **ANC** of L=10 and μ=0.001 and the calculated **SNR** value for this signal equal to 1.3 dB while Fig. 5-d shows the estimated speech signal by the proposed **TSANC** has a **SNR**=11.23 dB. From this Figure, it is clear that the quality of the processed speech signal by the proposed **TSANC** increases, thus the amount of noise reduction is increased also.

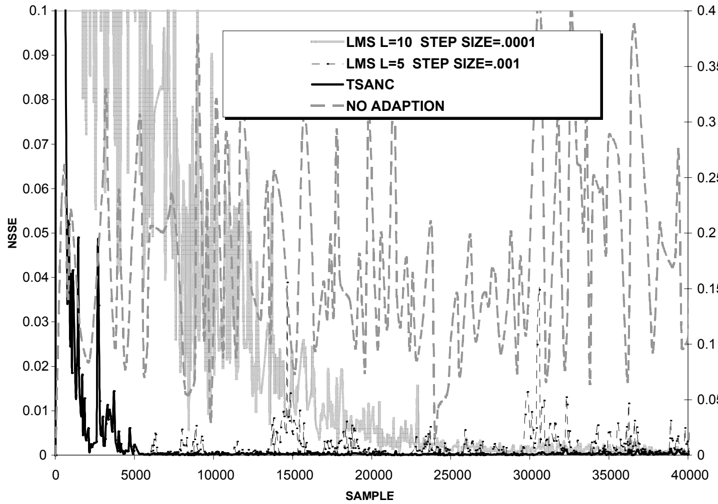

Fig. 4 Comparison between LMS and TSANC algorithm using the SNR of the noisy speech signal = –3.9 dB for sample from 0 to 40000.

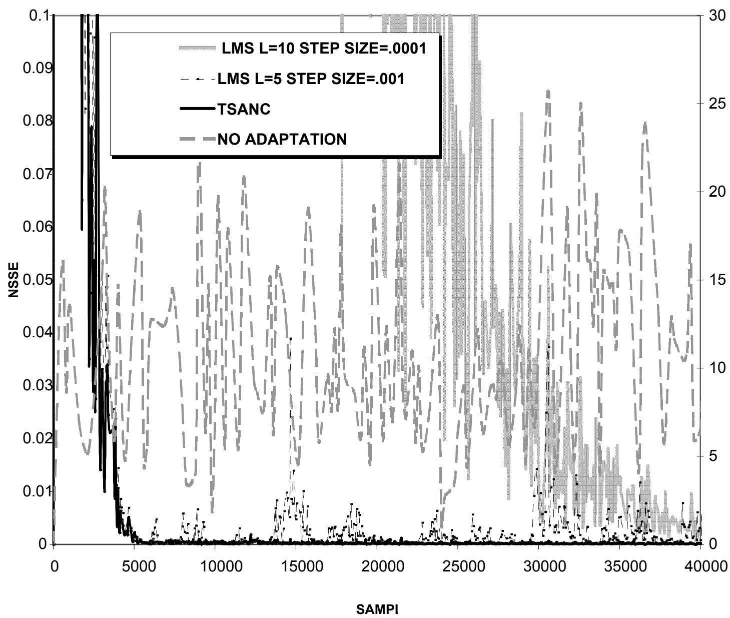

Figure (4.2) cont. : Comparison between LMS and TSANC algorithm using the SNR of the noisy speech signal = –12.9 dB for sample from 40000 to 80000

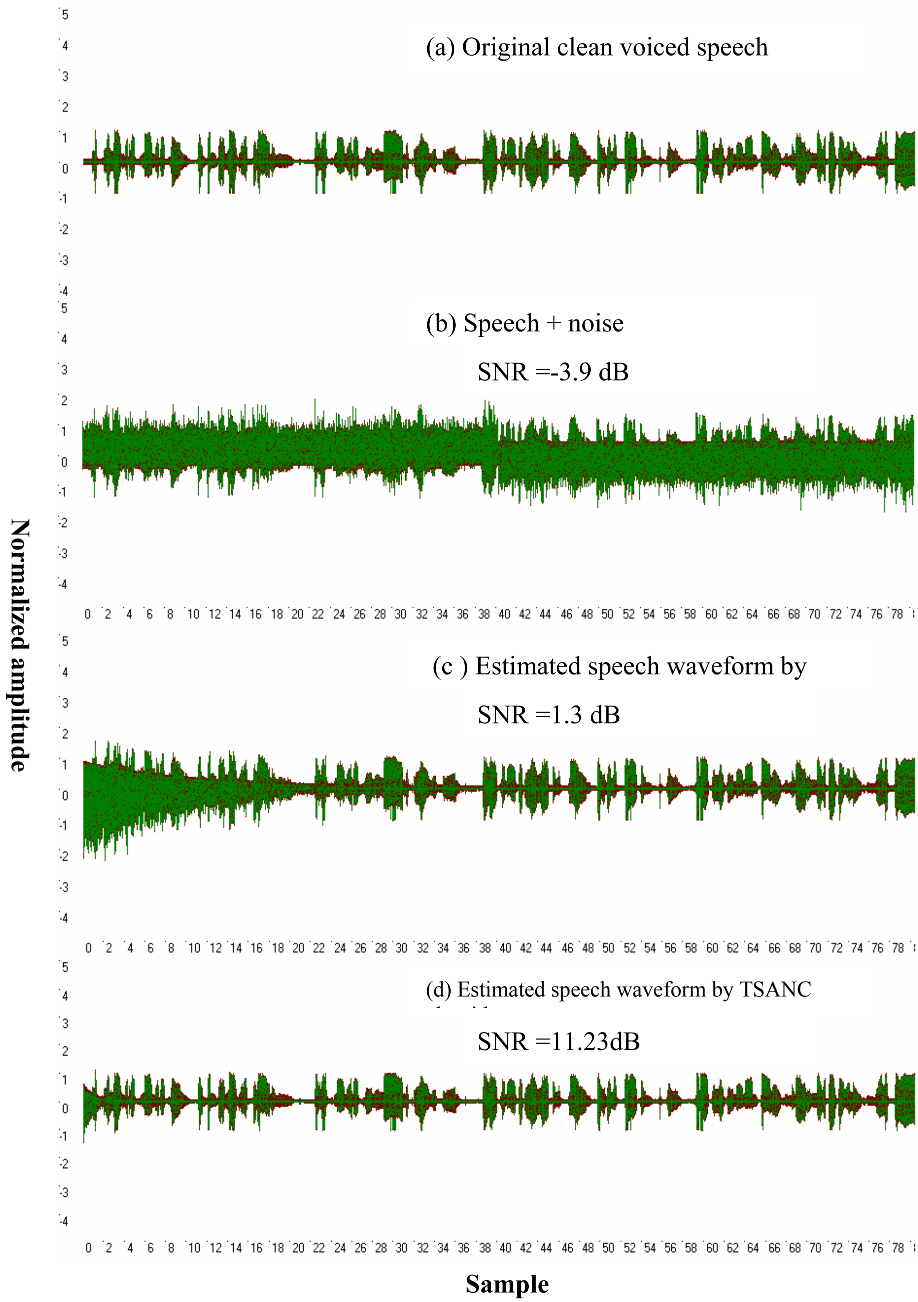

Fig. 5 The difference between estimated speech waveform of LMS and TSANC algorithm, using sampling rate of 8 kHz and the SNR of noisy speech signal =-3.9 dB.

4. CONCLUSION

The **TSANC** algorithm, which is proposed to achieve the coupling between the improvement in the performance of the steady state error and convergence rate, has a two cascade filters. The first one of the two filter use a large step size with low order to increase the convergence speed while the other filter use a small step size with a high order to decrease the steady state error. The computational operations required to the proposed technique have the same operations like the conventional **LMS** algorithm in case the two schemes are to have the same precision. It is found that the **TSANC** algorithm has a limited ability in tracking in nonstationary environment in a case of more changing in the noise level.

REFERENCES

1. Barnwell, T. P. , Nayebi, K, Richardson, C. H. , 1996, "Speech Coding ", New York :Wiley.
2. Boll, S., F., April.1979, "Suppression of Acoustic Noise in Speech Using Spectral Subtraction," IEEE Transaction on Acoustics, Speech, Signal Processing, vol. ASSP-27, pp.113-120.
3. Martins, C. and Piedade M., Oct.1993, "Fast Adaptive Noise Canceller Using the LMS Algorithm", proceeding of ICSPAT, vol.1, pp121-127.
4. Martins, C. and Piedade, M., Oct.1999, "Fast Multi-Band Adaptive Noise Canceller", proceeding of INESC, R. Alves Redol 9,1000 Lisboa, Portugal.
5. Sondhi, M., Schmidt, E. and Rabiner, L., October 1981, "Improving the Quality of a Noisy Speech Signal," Bell System Technical Journal, 60 (8).
6. Shawky, N. M., 2001, "Digital Adaptive Filters and Applications", Ph.D. thesis, Al-Azhar University, Egypt.

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