Estimation of speech absence uncertainty based on multiple linear regression analysis for speech enhancement

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We propose a novel approach to improve the performance of speech enhancement systems by using multiple linear regression to improve the technique of estimating the speech presence uncertainty. Conventional speech enhancement techniques use a fixed ratio of the \textit{a priori} probability of speech presence and speech absence, or determine the value of \( Q \) simply by comparing one particular parameter against a threshold in deriving the speech absence probability (SAP) associated with the speech presence uncertainty. To further improve the performance of the SAP, we attempt to adaptively change \( Q \) according to a linear model consisting of the regression coefficients obtained by results from multiple linear regression analysis and two principal parameters: \textit{a priori} SNR and the ratio between the local energy of the noisy speech and its derived minimum since these parameters correlate strongly with the value of \( Q \). Distinct values of \( Q \) for each frequency in each frame are consequently assigned in time which leads to improved tracking performance of speech absence uncertainty and thus better performance of the proposed speech enhancement compared to conventional approaches. The superiority of the proposed approach is confirmed through extensive objective and subjective evaluations under various noise conditions.

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1. Introduction

Because ambient noise drastically degrades the performance of speech processing systems, emerging applications in this field are demanding increasing performance in terms of ambient noise reduction in adverse environments. For example, the mobile phone system is particularly sensitive to various ambient noise environments involving nonstationary noise and low input signal-to-noise ratio (SNR). Early approaches based on the spectral weighting rule have been developed to achieve speech enhancement. These include Wiener filtering \cite{1}, minimum mean square error (MMSE) estimation \cite{2}, soft decision estimation \cite{3}, and MMSE log-spectral amplitude criteria \cite{5}. These approaches are further developed by using a soft decision scheme in which the speech absence probability (SAP) is derived based on the likelihood ratio test (LRT) and used for gain modification \cite{4,6}. The SAP plays an important role on the performance of speech processing systems. In practice, the spectral gain for noise suppression is modified by the SAP, which is estimated for each frequency bin in each frame on a Fourier transform domain. Furthermore, the soft decision-based schemes have been further improved by \cite{4} called the global soft decision.

This method is performed \textit{globally}: speech activity is determined for each frame rather than for each frequency bin, thereby providing a robust estimation of the SAP. In the soft decision-based technique, the ratio \( Q \) of the \textit{a priori} probability of speech presence and speech absence is the crucial parameter in deriving the SAP since \( Q \) must reflect the average ratio of speech presence and absence from the initial frame until the current frame. However, in most of conventional techniques for estimating the uncertainty of speech presence, the SAP is derived using a fixed \( Q \) for all frequency components in every frame. For instance, \( Q \) was set to 1 in order to address the worst-case in which speech and noise are equally likely to occur in \cite{1}. Also, \( Q \) was chosen as 0.2 based on the listening test as in \cite{2}, while the global soft decision method in \cite{4} adopted 0.0625 for the value of \( Q \).

Some previous work has considered ways to estimate and update \( Q \). Malah et al. \cite{6} derived an algorithm to assign distinct values of \( Q \) to different frequency bins for each frame by comparing the \textit{a posteriori} SNR with the given threshold. However, the \textit{a posteriori} SNR is sensitive to outliers under the time-varying noise condition. Soon et al. \cite{7} proposed a method to update the \textit{a priori} probability of speech absence by comparing the conditional probabilities of speech presence and speech absence. On the other hand, Cohen \cite{8} proposed the minima-controlled recursive averaging (MCRA) approach, which is known to be the successful noise power...
estimation due to its robustness to the type and intensity of environmental noises. In particular, the presence of speech in subbands is determined by Cohen’s parameter ($S_5$), which is the ratio between the local energy of noisy speech and its derived minimum. This algorithm is known to be computationally efficient, but it is insensitive to temporal variation. Recently, a method to track the a priori probability of speech absence was devised in [9] by using $S_5$ at the MCRA method instead of the $p$exp $\tau j1$: $p$exp $\tau j$ is the gain function of the MMSE estimator given in [4]; $p$ $\kappa$ $j$ $k$ are given by [4], [9] by using $S_5$.

In this paper, we propose a novel approach to control $Q$ based on multiple linear regression analysis by using the a priori SNR and the ratio $S_5$. Practically, the global soft decision-based speech enhancement is considered to be a target platform in which the SAP is derived based on $Q$ as well as the statistical model, in which the a priori SNR is estimated and is used to modify the spectral gain and update the noise power. Firstly, through an in-depth linear regression analysis, we investigate the extent to which $Q$ is correlated with the a priori SNR and $S_5$. This is achieved with the help of the Pearson’s correlation coefficient test [10,11], which is known to be efficient in estimating the correlation between two variables. Secondly, in an off-line training step, we apply the method of least squares to estimate the linear model’s regression coefficients of $Q$ on two parameters: a priori SNR and $S_5$. Finally, in an on-line processing step, $Q$ is adaptively determined and used to control the SAP depending on the values of the a priori SNR and $S_5$ to improve the overall performance of the proposed speech enhancement technique over conventional alternatives. We evaluate our proposed algorithm through extensive objective and subjective quality tests, which demonstrate the algorithm’s improved performance over conventional methods.

The rest of the paper is organized as follows. Section 2 gives a brief review of the techniques used for speech presence uncertainty estimation, and Section 3 presents the proposed method, which uses multiple linear regression analysis. Section 4 describes the experimental setup and results in detail; Section 5 presents conclusions.

2. Review of speech absence uncertainty estimation techniques

We first briefly review the notion of the soft decision-based method for estimating speech absence uncertainty. It is assumed that a noise signal $d(t)$ is added to a speech signal $x(t)$, with their sum being denoted as the noisy speech signal $y(t)$. By taking the discrete Fourier transform (DFT) of the noisy signal $y(t)$, we then have the following in the time-frequency domain:

$$Y(k, n) = X(k, n) + D(k, n),$$

where $k = 0, 1, \ldots, K - 1$ is the frequency bin and $n$ is the frame index. Given two hypotheses, $H_0$ and $H_1$, which indicate speech absence and presence, respectively, it is assumed that:

$$H_0 : Y(k, n) = D(k, n),$$
$$H_1 : Y(k, n) = X(k, n) + D(k, n).$$

Based on the complex Gaussian probability distribution assumption of the clean speech and noise spectra, the probability density functions (PDFs) conditioned on the two hypotheses $H_0$ and $H_1$ are given by [4]:

$$p(Y(k, n)|H_0) = \frac{1}{\pi \lambda_2(k, n)} \exp \left\{ -\frac{|Y(k, n)|^2}{\lambda_2(k, n)} \right\},$$

$$p(Y(k, n)|H_1) = \frac{1}{\pi \lambda_2(k, n) + \lambda_2(k, n)} \exp \left\{ -\frac{|Y(k, n)|^2}{\lambda_2(k, n) + \lambda_2(k, n)} \right\},$$

where $\lambda_2(k, n)$ and $\lambda_2(k, n)$ denote the variances of the clean speech and noise, respectively. If the spectral component of each frequency bin is assumed to be statistically independent, the SAP $P(H_0|Y(k, n))$, which is conditioned on the current observation, is derived such that [1,4]:

$$P(H_0|Y(k, n)) = \frac{p(Y(k, n)|H_0)P(H_0)}{p(Y(k, n)|H_0)P(H_0) + p(Y(k, n)|H_1)P(H_1)} = \frac{1}{1 + \pi \lambda_2(k, n) \lambda_2(k, n)} A(Y(k, n)), \quad (5)$$

where $P(H_0) = 1 - P(H_1)$ is the a priori probability of speech absence. Substituting (3) and (4) into (5), the likelihood ratio $A(Y(k, n))$ at the $k$th frequency is expressed as follows [4]:

$$A(Y(k, n)) = \frac{p(Y(k, n)|H_1)}{p(Y(k, n)|H_0)} = \frac{1}{1 + \lambda_2(k, n)} \exp \left\{ \frac{\gamma(k, n) \xi(k, n)}{1 + \xi(k, n)} \right\}, \quad (6)$$

where

$$\xi(k, n) = \frac{\lambda_2(k, n)}{\lambda_2(k, n)},$$

$$\gamma(k, n) = \frac{|Y(k, n)|^2}{\lambda_2(k, n)},$$

where $\xi(k, n)$ and $\gamma(k, n)$ are called the a priori SNR and the a posteriori SNR, respectively. Also, $P(H_1)/P(H_0) = Q$ in (5) is defined as the ratio of the a priori probability of speech presence and absence [4]. By using the SAP mentioned above, the spectrum of enhanced speech signal, $\hat{X}(k, n)$, can be obtained by applying a parametric gain to each spectral component of the noisy speech signal. Here, we employ the minimum mean square error (MMSE) estimator based on SAP as follows:

$$\hat{X}(k, n) = (1 - P(H_0)|Y(k, n)) |G_{\text{MMSE}}(\hat{\xi}(k, n), \hat{\gamma}(k, n))Y(k, n),$$

where $G_{\text{MMSE}}$ is the gain function of the MMSE estimator given in [2,4]. Also, estimate of the a priori SNR $\hat{\xi}(k, n)$ and a posteriori SNR $\hat{\gamma}(k, n)$ are obtained by using the decision-directed method [2] with $\alpha_{00} = 0.99$ and long-term smoothing with $\xi_{00} = 0.98$, respectively, as follows [4]:

$$\hat{\xi}(k, n) = \alpha_{00} \frac{\hat{X}(k, n - 1)^2}{\lambda_2(k, n - 1)} + (1 - \alpha_{00})U[\gamma(k, n) - 1],$$

$$\hat{\gamma}(k, n) = \frac{|Y(k, n)|^2}{\lambda_2(k, n)},$$

where

$$\lambda_2(k, n) = \xi_{00} \lambda_2(k, n - 1) + (1 - \xi_{00})|Y(k, n)|^2,$$

when the speech signal is not present, and $U[z] = z$ if $z \geq 0$ and $U[z] = 0$ otherwise.

As mentioned above, some approaches assigned a fixed value of $Q$ [1–4], but $Q$ can be differently determined for each frequency bin in each frame in the method of Malah et al. [6] by comparing the a posteriori SNR with a given threshold. Also, $Q$ can be adaptively determined by the ratio of the local energy of noisy speech and its derived minimum in [8]. Indeed, this method is inherently based on the MCRA approach, in which the decision rule for the presence of speech is derived as

$$S_1(k, n) \begin{cases} \frac{\xi_{00}}{\lambda_{00}} = 1, & \text{if } \xi_{00} = 0; \\ \geq \delta, & \text{otherwise}. \end{cases} \quad (13)$$

where $\delta$ is a given threshold and $I(k, n)$ is an indicator function. $S_1(k, n)$ is actually derived by $|Y(k, n)|^2/S_{\text{min}}(k, n)$ in which $S_{\text{min}} = \min$
\( \{(Y[k, n - L + 1]^2, Y[k, n - L + 2]^2, \ldots, Y[k, n]^2) \}. \) Using \( l(k, n) \), a method to track \( Q \) is devised as in the method of Lee et al. [9] as follows:

\[
Q(k, n) = x_p Q(k, n - 1) + (1 - x_p) l(k, n),
\]

where \( x_p = 0.2 \) is a smoothing parameter.

3. Enhanced speech absence probability based on multiple linear regression technique

As stated in the previous section, previous work has proposed using either a fixed value of \( Q \), or an adaptive \( Q \) according to an indicating function derived from the MCRA technique [4,8]. In our approach, we devise a novel method to find \( Q \) adaptively based on multiple linear regression analysis (MLRA) which is an outperforming technique for predicting the continuous outputs with two or more variables when given observations can be modeled by a linear function [10,12]. There exist any other modeling techniques such as Gaussian mixture regression, nonlinear regression, and deep neural network [13–15]. However, these are computationally burdensome in estimating even a few coefficients. For this reason, we select the efficient way to predict \( Q \) based on the MLRA technique. The main objective of the present study is to show that this technique of least squares using the sum of squares of the error term, estimation of regression coefficients is performed based on the population mean of \( Q \), \( \xi \), and \( S_i \), respectively. Using this technique, the \( a \) priori SNR is shown to be highly correlated with \( Q \) with \( \rho_1 = 0.85 \) (as in Fig. 1), which is considered to be high [10,11] and \( S_i \) is also highly correlated with \( Q \) with \( \rho_2 = 0.86 \) (as in Fig. 2), which shows the selected two parameters can be successfully used as the independent variables for predicting \( Q \). Based on this, supposing that there are \( N \) data points \( \{(Y[i, X_i]\} \), where \( i = 1, 2, \ldots, N \), we build the basic model for the simple linear regression as given by

\[
Y_i = \beta_0 + \beta_1 X_i + \epsilon_i,
\]

where \( \beta_0 \) and \( \beta_1 \) are the regression coefficients and \( \epsilon_i \) is the error. Note that this model provides the best fit for the data points where ‘best’ is understood in terms of the least-squares approach, with the best fit being that which minimizes the sum of the squared residuals between the measured variable and the hypothesis from the linear regression model. Extending this equation into the multiple linear regression model [10,12], our approach for using two independent variables, \( \xi \) and \( S_i \), can be expressed as follows:

\[
Q_i = \beta_0 + \beta_1 \xi + \beta_2 S_i + \epsilon_i,
\]

where \( \beta_0, \beta_1, \) and \( \beta_2 \) are the constant regression coefficients. The estimation of regression coefficients is performed based on the method of least squares using the sum of squares of the error term, \( E \), which is represented by

\[
E = \sum_{i=1}^{N} (Q_i - (\beta_0 + \beta_1 \xi + \beta_2 S_i))^2,
\]

where \( N \) denotes the total number of observations and the regression coefficients are obtained by differentiating \( E \) partially with respect to \( \beta_0, \beta_1, \) and \( \beta_2 \) and setting to zero such that

![Fig. 1. Visualizing regression surfaces through a scatter plot of Q versus \( \xi \).](image-url)
In time, \( b_0, b_1, \) and \( b_2 \) are estimated using the solutions of the normal equations [10]. These normal equations can be expressed as a vector–matrix form as follows:

\[
\begin{bmatrix}
1 & \xi_1 & S_{r1} \\
1 & \xi_2 & S_{r2} \\
\vdots & \vdots & \vdots \\
1 & \xi_N & S_{rN}
\end{bmatrix}
\]

\[=\]

\[
X = \begin{bmatrix}
1 \\
1 \\
\vdots \\
1
\end{bmatrix}
\begin{bmatrix}
\xi_1 \\
\xi_2 \\
\vdots \\
\xi_N
\end{bmatrix}
\]

\[
X^T = \begin{bmatrix}
1 & 1 & \ldots & 1
\end{bmatrix}
\begin{bmatrix}
Q_1 \\
Q_2 \\
\vdots \\
Q_N
\end{bmatrix}
\]

where \( X \) and the vector form of the least square estimator of \( \beta \) and true \( Q \) are denoted as \( \hat{\beta} = [\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2]^T \) and \( Y = [Q_1, Q_2, \ldots, Q_N]^T \), respectively. Since the regression coefficients are obtained from the above process, we thus obtain the estimate of \( Q(k,n) \) according to the following regression equation.

\[\hat{Q}(k,n) = \hat{\beta}_0 + \hat{\beta}_1 \xi(k,n) + \hat{\beta}_2 S_r(k,n),\]

where the estimate of \( Q(k,n) \) is adaptively changed according to the estimates of \( \xi(k,n) \) [4] and \( S_r(k,n) \) [8] which are updated by the estimated noise power. By substituting the estimate of \( Q \) to (5), the SAP can be calculated. The use of the multiple regression technique could improve the SAP performance if the estimate of \( Q \) more closely resembles the true \( Q \). Indeed, by comparing the estimates of \( Q \) by the proposed method with the true \( Q \), it is seen that \( Q \) obtained from the proposed algorithm indeed looks more accurate than that derived from the conventional algorithms as shown in Fig. 3. As a result, it is expected precisely estimated \( Q \) leads to increase the performance of speech enhancement.

4. Experimental results

Our performance evaluation consisted of two parts. Firstly, we compared the objective speech quality of the proposed algorithm to that of Malah’s algorithm [6] and that of Cohen’s algorithm.
We then performed a subjective quality test and a study of speech spectrograms. Unlike the training database, we used the speech data taken from the TIMIT database [18] for checking the sensitivity of the training data to the overall algorithm, which included 1344 phrases spoken by 112 male and 56 female speakers, with each phrase consisting of two different meaningful utterances. These files having various length from 2 s to 14 s, were collected at a sampling rate of 8 kHz, and had frames 10 ms long. To the clean speech waveforms, we added four types of noise from the NOISEX-92 database [19]: babble, car, office, and street noises, each with SNRs of 5, 10, and 15 dB. Also, we included two noises such as destroyer-operation and factory, which were not used in the training for ensuring the robust performance of the proposed algorithm. The regression coefficients applied in the proposed method were those obtained from the actual number of data $N = 40,000$ as in (23): $\hat{\beta}_0 = 0.248, \hat{\beta}_1 = 0.479$, and $\hat{\beta}_2 = 0.382$. Also, the experiment was implemented using the experimentally optimized parameter values from the methods of Malah [6] and Cohen [8]: $\gamma_{TH} = 0.8$, $\delta = 5$, and $L = 100$. These regression coefficients and these two parameters extracted from the noisy speech inputs were used to derive the estimate of $Q$ in (23), allowing us to improve the previous methods for estimating SAP.

Among our evaluation methods, the first was two well-known objective tests: the ITU-T P.862 perceptual evaluation of speech quality (PESQ) [20] and the second was the composite measure ($C_{\text{ref}}$) proposed by Hu and Loizou [11]. Note that $C_{\text{ref}}$ is known to have a strong correlation with the overall perceptual speech quality. The proposed method outperformed the conventional two algorithms in every testing condition as Table 1 summarizes the results of the PESQ and $C_{\text{ref}}$ tests. The performance gain was not large, but was quite consistent, showing that our proposed approach reliably improves the performance regardless of the given conditions. In particular, it is noted that the consistent

### Table 1
Comparison of PESQ and $C_{\text{ref}}$ scores in various noise environments (95% confidence interval).

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Babble</td>
<td>2.30 ± 0.01</td>
<td>2.60 ± 0.01</td>
<td>2.97 ± 0.01</td>
<td>2.46 ± 0.01</td>
<td>2.88 ± 0.01</td>
<td>3.42 ± 0.01</td>
</tr>
<tr>
<td></td>
<td>2.50 ± 0.01</td>
<td>2.91 ± 0.01</td>
<td>3.44 ± 0.01</td>
<td>2.73 ± 0.01</td>
<td>3.08 ± 0.01</td>
<td>3.47 ± 0.01</td>
</tr>
<tr>
<td></td>
<td>2.91 ± 0.01</td>
<td>3.47 ± 0.01</td>
<td>3.47 ± 0.01</td>
<td>2.75 ± 0.01</td>
<td>3.15 ± 0.01</td>
<td>3.50 ± 0.01</td>
</tr>
<tr>
<td></td>
<td>2.50 ± 0.01</td>
<td>3.47 ± 0.01</td>
<td>3.47 ± 0.01</td>
<td>2.75 ± 0.01</td>
<td>3.15 ± 0.01</td>
<td>3.50 ± 0.01</td>
</tr>
</tbody>
</table>

### Table 2
Comparison of MOS scores in various noise environments (95% confidence interval).

<table>
<thead>
<tr>
<th>Noise</th>
<th>Method</th>
<th>SNR (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>5</td>
</tr>
<tr>
<td>Babble</td>
<td>Malah [6]</td>
<td>2.08 ± 0.03</td>
</tr>
<tr>
<td></td>
<td>Cohen [8]</td>
<td>2.12 ± 0.03</td>
</tr>
<tr>
<td></td>
<td>Proposed</td>
<td>2.16 ± 0.03</td>
</tr>
<tr>
<td>Car</td>
<td>Malah [6]</td>
<td>2.74 ± 0.02</td>
</tr>
<tr>
<td></td>
<td>Cohen [8]</td>
<td>2.66 ± 0.02</td>
</tr>
<tr>
<td></td>
<td>Proposed</td>
<td>2.83 ± 0.02</td>
</tr>
<tr>
<td>Office</td>
<td>Malah [6]</td>
<td>2.41 ± 0.02</td>
</tr>
<tr>
<td></td>
<td>Cohen [8]</td>
<td>2.34 ± 0.03</td>
</tr>
<tr>
<td></td>
<td>Proposed</td>
<td>2.48 ± 0.03</td>
</tr>
<tr>
<td>Street</td>
<td>Malah [6]</td>
<td>2.71 ± 0.02</td>
</tr>
<tr>
<td></td>
<td>Cohen [8]</td>
<td>2.81 ± 0.02</td>
</tr>
<tr>
<td></td>
<td>Proposed</td>
<td>2.87 ± 0.02</td>
</tr>
<tr>
<td>Destroyer-operation</td>
<td>Malah [6]</td>
<td>2.02 ± 0.02</td>
</tr>
<tr>
<td></td>
<td>Cohen [8]</td>
<td>2.11 ± 0.02</td>
</tr>
<tr>
<td></td>
<td>Proposed</td>
<td>2.17 ± 0.02</td>
</tr>
<tr>
<td>Factory</td>
<td>Malah [6]</td>
<td>2.21 ± 0.03</td>
</tr>
<tr>
<td></td>
<td>Cohen [8]</td>
<td>2.29 ± 0.03</td>
</tr>
<tr>
<td></td>
<td>Proposed</td>
<td>2.37 ± 0.03</td>
</tr>
</tbody>
</table>
A performance improvement was observed for the open set of noises such as destroyer-operation and factory, which confirms the robustness of our approach.

To validate the performance of the proposed algorithm, we conducted mean opinion score (MOS) tests on a number of the aforementioned noisy speech samples. Ten listeners performed listening tests and each listener gave for each test sentence a score from one to five: 5 (Excellent), 4 (Good), 3 (Fair), 2 (Poor) and 1 (Bad). All the scores were then averaged to yield the final MOS results. This score represents the listeners' global appreciation of each method's residual noise and speech distortion. As a result as in Table 2, the proposed approach scored comparably to or outperformed the conventional methods in terms of overall subjective quality under the various noise environments. This is because the proposed method reduces the distortion of speech through improved SAP, while also reducing background noise. The subjective listening test confirms the superiority of the proposed technique over the other algorithms studied.

By an evidence like an example of the spectrogram for the case of the car noise as in Fig. 4, the proposed algorithm reduces residual noise well while preserving the speech spectra. This shows that speech enhanced with the proposed method sounds more pleasant referring to the subjective MOS results in Table 2 and residual noise is perceptually more comfortable (Fig. 4c and d).

5. Conclusions

We proposed a novel approach to improve the performance of the SAP using the values of $Q$ obtained from the MLRA technique based on the strong correlation of the selected parameters ($S$ and $S_r$) to the value of $Q$. This approach enables the SAP to be estimated more accurately under various noisy conditions by adaptively changing $Q$ based on the multiple linear regression analysis technique. In both objective and subjective quality tests over various noise types and SNR levels, the proposed method yielded performance superior to that of conventional methods.

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