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# A Novel Speech/Noise Discrimination Method for Embedded ASR System

**Bian Wu**
*Institute of Image Processing & Pattern Recognition, Shanghai Jiaotong University, Shanghai 200030, China*
*Email: wu_bian@sjtu.edu.cn*

**Xiaolin Ren**
*Motorola Labs China Research Center, Shanghai 200041, China*
*Email: xiaolin.ren@motorola.com*

**Chongqing Liu**
*Institute of Image Processing & Pattern Recognition, Shanghai Jiaotong University, Shanghai 200030, China*
*Email: liuchqing@263.net*

**Yaxin Zhang**
*Motorola Labs China Research Center, Shanghai 200041, China*
*Email: yaxin.zhang@motorola.com*

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The problem of speech/noise discrimination has become increasingly important as the automatic speech recognition (ASR) system is applied in the real world. Robustness and simplicity are two challenges to the speech/noise discrimination method for an embedded system. The energy-based feature is the most suitable and applicable feature for speech/noise discrimination for embedded ASR system because of effectiveness and simplicity. A new method based on a noise model is proposed to discriminate speech signals from noise signals. The noise model is initialized and then updated according to the signal energy. The experiment shows the effectiveness and robustness of the new method in noisy environments.

**Keywords and phrases:** noise robustness, speech/noise discrimination, automatic speech recognition.

## 1. INTRODUCTION

The problem of speech/noise discrimination has become increasingly important as the automatic speech recognition (ASR) system is applied in the real world. Robustness and simplicity are the basic requirements of a speech/noise discrimination method for an embedded ASR system. The discrimination method should be robust in various noisy environments at various SNRs. Low complexity is another challenge because of the requirement of real-time and the limitation of embedded system. Early algorithms [1, 2] fail in low SNR environments. Many recently proposed methods, such as [3, 4, 5, 6], are not designed deliberately for real-time embedded system. Some employ expensive methods, such as higher-order statistics (HOS) [3], which improve the robustness at the cost of greatly increased computational complexity. Others propose some low-cost methods, such as entropy [4], which is only effective in some environments.

## 2. THE NOISE MODEL

The energy-based feature is the most suitable and applicable feature for speech/noise discrimination for embedded ASR system because of effectiveness and simplicity. The full-band energy fails at low SNR. Hereby the subband energy [7] is proposed to improve the robustness. Speech shows characteristically uneven distribution of energy in different frequencies, and the characteristic of noise is alien to that of speech. From the angle of the background noise, the intrusion of speech will cause the variation of the spectrum characteristic.

The energy spectrum of the noise is modeled by a multi-dimensional Gaussian distribution $N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$. $\boldsymbol{\Sigma}$ is assumed to be a diagonal matrix for the sake of simplicity. Then the noise model can be expressed as $N(\boldsymbol{\mu}, \boldsymbol{\sigma}^2)$. If there are $J$ subbands,

$$\begin{aligned} \boldsymbol{\mu} &= \left(\mu_1 \;\; \mu_2 \;\; \mu_3 \;\; \cdots \;\; \mu_J\right)', \\ \boldsymbol{\sigma}^2 &= \left(\sigma_1^2 \;\; \sigma_2^2 \;\; \sigma_3^2 \;\; \cdots \;\; \sigma_J^2\right)'. \end{aligned} \tag{1}$$

A score is computed for each frame as such:

$$\text{Score}\left(\mathbf{O}_i\right) = \frac{1}{\sqrt{2\pi}\boldsymbol{\sigma}}\mathbf{e}^{-(\mathbf{O}_i-\boldsymbol{\mu})^2/2\boldsymbol{\sigma}^2}, \tag{2}$$

where $\mathbf{O}_i = (O_{i,1}\ O_{i,2}\ O_{i,3}\ \cdots\ O_{i,J})'$ is the energy spectrum vector for each frame.

Therefore if the spectral character of the frame is similar to that of the noise, the score will be high, and vice versa. The frequency energy in 250–3500 Hz is used because the bulk of energy of human speech exists in the band. Then the band 250–3500 Hz is divided into several subbands evenly. The energy spectrum vector $\mathbf{O}_i$ consists of the spectral energy in each band.

Without a priori knowledge of the characteristic of noise, the noise model must be initialized according to the working environment. In practice we assume that there is at least 100–250 millisecond pure noise preceding the actual speech. By using these frames the noise model can be easily seeded. Moreover, if current frame is classified as noise, the model will be updated by the energy spectrum of the frame. This procedure, which utilizes an iterative method, makes the model follow up the variation of the noise and be a more sufficient statistics to the character of the environmental noise. The updated formula is

$$\begin{aligned}\boldsymbol{\mu}_{n+1} &= \frac{\boldsymbol{\mu}_n \cdot n + \mathbf{N}_{n+1}}{n+1},\\ \boldsymbol{\sigma}^2_{n+1} &= \frac{(n-1)\cdot\boldsymbol{\sigma}^2_n + \left(\mathbf{N}_{n+1}-\boldsymbol{\mu}_n\right)^2}{n} - \left(\boldsymbol{\mu}_{n+1}-\boldsymbol{\mu}_n\right)^2,\end{aligned} \tag{3}$$

where $\boldsymbol{\mu}_{n+1}$, $\boldsymbol{\sigma}^2_{n+1}$ and $\boldsymbol{\mu}_n$, $\boldsymbol{\sigma}^2_n$ are the mean vector and variance vector after and before updating, respectively, $n$ the number of noise frames before the update, and $\mathbf{N}_{n+1}$ the noise frame to update the model. In real environments the background noise varies. It is reasonable to fix $n$ when it is greater than a certain number, which we choose as 32, so that the update procedure needs a short-period memory rather than remembering the whole utterance. Therefore $\boldsymbol{\mu}_{n+1}$ and $\boldsymbol{\sigma}^2_{n+1}$ are in fact the maximum likelihood estimator (MLE) in a slipping window of noise frames. By these means, the algorithm will work well for both long-term stationary and time-varying noise.

The speech/noise discrimination does not add much to the computational cost of the overall ASR system. The energy spectrum is the interproduct of a standard front end. The logarithm form of the noise model score is employed instead of formula (2):

$$\begin{aligned}\text{Score}\left(\mathbf{O}_i\right) &= \frac{\left(\mathbf{O}_i-\boldsymbol{\mu}\right)^2}{\boldsymbol{\sigma}^2} + \ln\left(\boldsymbol{\sigma}^2\right)\\ &= \sum_j\left[\frac{\left(O_{i,j}-\mu_j\right)^2}{\sigma_j^2} + \ln\left(\sigma_j^2\right)\right],\end{aligned} \tag{4}$$

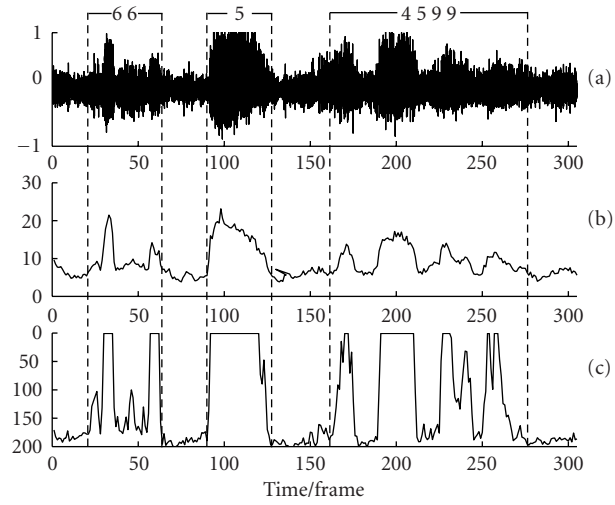


Figure 1: Contour curves of short-time energy and noise model score: (a) waveform (SNR < 10 dB), (b) short-time energy, and (c) noise model score.

where $O_{i,j}$ is the $j$th subband of the $i$th frame, $\mu_j$ and $\sigma_j^2$ the $j$th subbands of the $\boldsymbol{\mu}$ vector, and $\boldsymbol{\sigma}^2$ vector, respectively. The computational complexity of the score can be lowered. In fact the conversion to logarithm form is not optional but mandatory. For fixed-point computation, the logarithm form can get better precision than the original one.

Moreover, the division of subband does not increase the cost because no mathematical computation is imported. The iterative update procedure requires a few calculations, which also satisfies the requirement of low cost.

Figure 1 shows the waveform and the contour curves of short-time energy and noise model score of an English digit string "6654599." It can be seen that the noise model score outperforms the short-time energy in pattern classification because of a much greater distance between noise frame and speech frame, and it can also achieve a good discrimination between fricative frame and noise frame.

## 3. EXPERIMENT

Li et al. proposed a robust method to discriminate speech from noise in [8]. The method is also designed deliberately for real-time implementation. The method is based on a filter, which can be operated as a moving-average filter in the full-band energy feature:

$$F(t) = \sum_{i=-W}^{W} h(i)g(t+i), \tag{5}$$

where $g(\cdot)$ is the energy feature, $h(\cdot)$ the filter coefficients,

$W$ the filter size, and $t$ the current frame number. Here, we set $W = 13$.[1] The filter has positive response to an upward sloping shape, negative response to a downward sloping shape, and a near-zero response to a flat shape. Therefore $F(t) > T_U > 0$ indicates a beginning point and $F(t) < T_L < 0$ an ending point. The frames between beginning and ending points are classified as speech.

Experiments had been carried out to evaluate the proposed method. The noise model score was computed for each frame and it was then compared with a threshold. According to formula (4), a frame was classified as speech when its score was greater than the threshold.

The discrimination method will be used in mobile phone, which will work in any real world environment. So the evaluation database was collected from mobile cellular phone with 8 kHz sampling rate in various natural noisy environments. The environments include office, park, airport, street, and car at different speeds. The noise in the office environment is usually air-condition fan noise, the noise in the park environment is usually wind noise, and the noise in the airport and the street environment is usually background babble noise. But the airport environment has acoustic echo effect. The noise in the car environments is usually engine noise at different speeds such as idle, 10 mph, 45 mph, and variable speed. The database contains only pure digit strings and the string lengths vary from one to eight. There are four sets, quoted as 01 to 04, in the database. Each set includes more than 5000 strings (more than 20 000 digits) in all environments mentioned above. Also the database is collected for different persons. From 01 to 03 the average SNRs are 15 dB, 10 dB, and 5 dB, respectively, and noise level is stable in the duration of each utterance. In 04 the average SNR is also 5 dB, but the noise level varies in the duration of each utterance. The proposed method was compared with Li's method. The results of the two methods were compared to the hand label. Though the two methods give the discriminating results in different ways, where one gives endpoints, and the other frame classification results, they are essentially the same.

There are two kinds of error: one is misclassification of noise as speech (error I) and the other is misclassification of speech as noise (error II). The fault risks of misclassification between noise and speech are quite different. Error II can result in a fatal deletion error. However, even if noise is mistaken for speech, we still have chances to reduce the fault risk by later processing. Therefore misclassifying noise as speech is preferred to misclassifying speech as noise. Then the classifier should satisfy the following formula:

$$p(\mathbf{S} \mid \mathbf{O}_i \in \mathbf{N}) > p(\mathbf{N} \mid \mathbf{O}_i \in \mathbf{S}). \tag{6}$$

[1]The coefficients of the half of the filter are $[h(0) \cdots h(13)] = [0, 0.350840, 0.643411, 0.850980, 0.967861, 0.999647, 0.957534, 0.855350, 0.708377, 0.533398, 0.349536, 0.179580, 0.051519, 0.000006]$, and the other half coefficients are set according to $h(-i) = -h(i)$.

The experimental results are shown in Figure 2, where Figures 2a–2d show the ROC curves of the two methods in sets 01–04, respectively. According to formula (6), only the part of the ROC curve above the diagonal line is relevant to the current study. It is seen from Figure 2 that for each set the ROC curve of the model-based method is always above that of the filter-based method in the part above the diagonal line. So the model-based method outperforms the filter-based one in each set.

All the ROC curves of the model-based method are then put into one figure (Figure 3). It is seen from Figure 3 that though the average SNR in each dataset is quite different, the ROC curves of the model-based method do not show great difference, especially the part above the diagonal line, which means that the performance of the model-based method does not vary with the variation of the SNR.

In the above experiment, the frequency band 250–3500 Hz is divided into 26 subbands evenly. The number of the bands will determine the proposed method in terms of performance and cost. Though the performance improves as the number of the subbands increases, the computational cost also increases. So there is a trade-off between performance and cost. Table 1 shows the correct rate $p(\mathbf{S} \mid \mathbf{O}_i \in \mathbf{S})$ of the model-based method in three cases of the subbands number. The thresholds in the three cases are set according to the same method, which makes the operating point of the ROC curve above the diagonal line. The computational cost of 26 subbands is about one forth of that of 104 subbands, while the correct rate of each set decreases slightly. When the number of subbands decreases from 26 to 1 (short-term full-band energy), the performance degrades greatly. Good balance is shown between the cost and performance in the 26 subband case.

## 4. CONCLUSIONS

We propose a robust method for speech/noise discrimination in noisy environments. The experiment shows that the new method outperforms the filter-based method proposed by Li in each dataset. By setting a proper operating point on the ROC curve, the performance of the method can satisfy formula (6). The method can be incorporated with some logic such as the automaton in [8] to make a final discrimination. The method has been incorporated into an SI open-vocabulary ASR on Compaq iPAQ. The memory cost of fixed-point implementation does not exceed 30 KB in comparison with about 300 KB used by overall system.

From the experiment results, we realize that the new method generates less gain in the nonstable SNR situation. In 26 subband case it generates 90.02% correct rate in set 03, compared with only 87.26% in set 04, which in fact has the same average SNR as set 03. This indicates that we may need a more robust noise model update scheme in the future work.

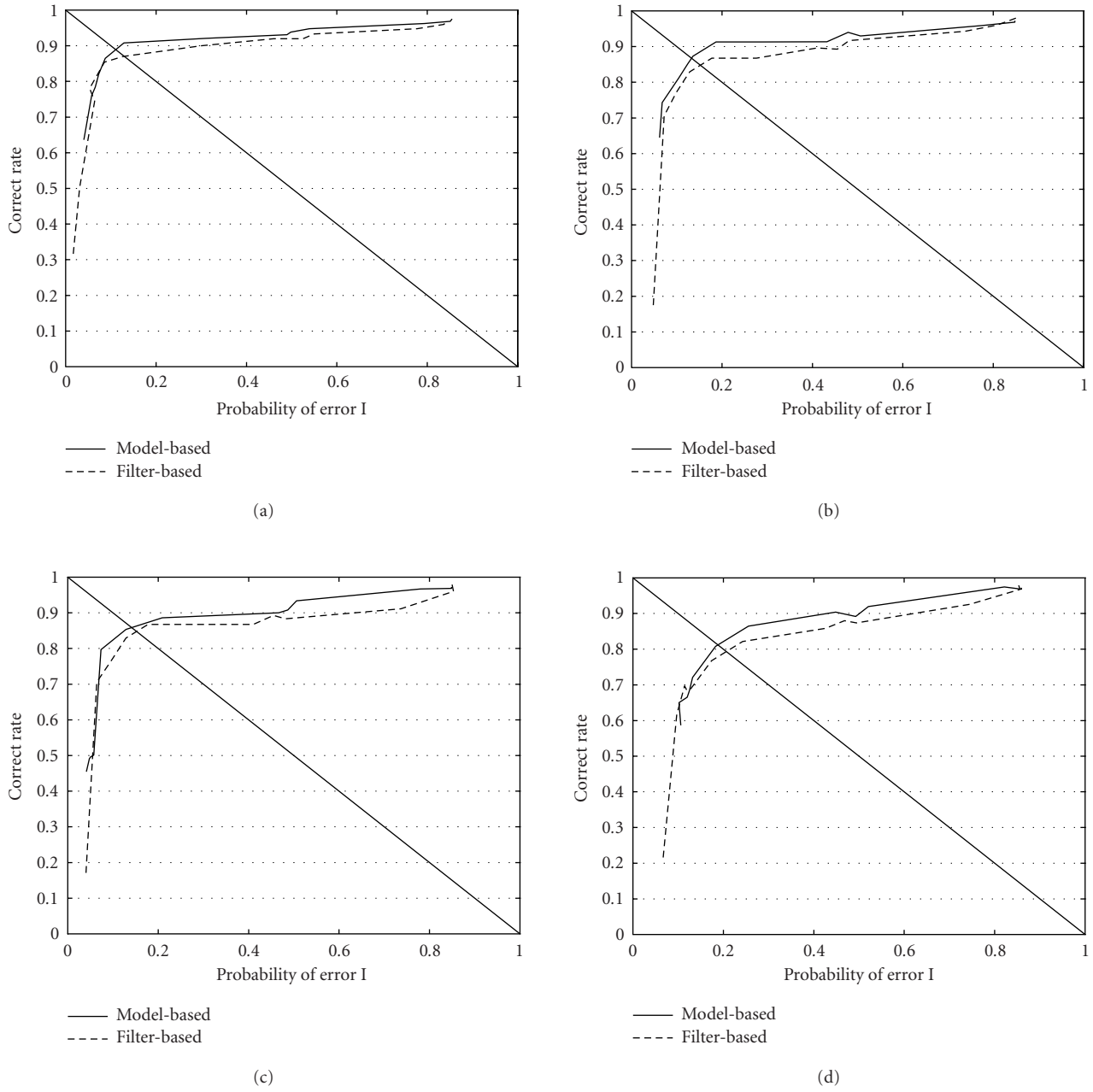


Figure 2: Comparison of ROC curves of two methods in each dataset.

## APPENDIX

## DERIVATION OF FORMULA (3)

For a Gaussian distribution

$$p(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2}, \tag{A.1}$$

$$\hat{\mu} = \frac{\sum x_i}{n}, \tag{A.2}$$

$$\hat{\sigma}^2 = \frac{\sum (x_i - \hat{\mu})^2}{n} \tag{A.3}$$

are the MLEs of mean and variance, respectively. An unbiased estimator that converges more closely to the true value as the sample size increases is called a consistent estimator. The mean estimator (A.2) is also an unbiased and consistent estimator. The (A.3) of the Gaussian distribution was obtained using MLE. This estimator of the true variance is a biased one. The consistent estimate of the variance is given by

$$\hat{\sigma}_c^2 = \frac{\sum (x_i - \hat{\mu})^2}{n-1}. \tag{A.4}$$

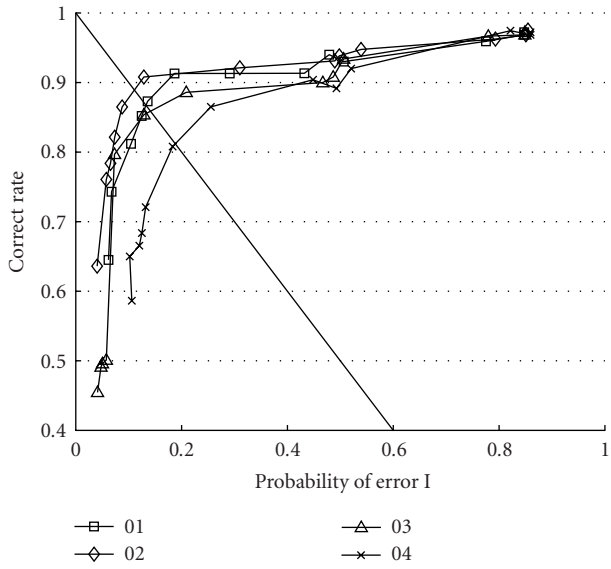


Figure 3: Comparison of ROC curves of the proposed method.

Table 1: The correct rate (%) in different conditions of the sub-bands numbers.

| Sets | 1 | 26 | 104 |
|---|---|---|---|
| 01 | 80.25 | 91.23 | 92.53 |
| 02 | 77.39 | 90.85 | 91.96 |
| 03 | 76.24 | 90.02 | 90.48 |
| 04 | 70.34 | 87.26 | 90.01 |

Note that for larger values of $n$, $\hat{\sigma}^2 = \hat{\sigma}_c^2$.

$$\hat{\mu}_n = \frac{\sum_n x_i}{n},$$

$$\hat{\mu}_{n+1} = \frac{\sum_{n+1} x_i}{n+1} = \frac{\sum_n x_i + x_{n+1}}{n+1} = \frac{n \cdot \hat{\mu}_n + x_{n+1}}{n+1},$$

$$\hat{\sigma}_n^2 = \frac{\sum_n (x_i - \hat{\mu}_n)^2}{n-1},$$

$$\begin{aligned}
\hat{\sigma}_{n+1}^2 &= \frac{\sum_{n+1} (x_i - \hat{\mu}_{n+1})^2}{n} = \frac{\sum_n (x_i - \hat{\mu}_{n+1})^2 + (x_{n+1} - \hat{\mu}_{n+1})^2}{n} \\
&= \frac{\sum_n (x_i - \hat{\mu}_n + \hat{\mu}_n - \hat{\mu}_{n+1})^2 + (x_{n+1} - \hat{\mu}_n + \hat{\mu}_n - \hat{\mu}_{n+1})^2}{n} \\
&= \frac{(n-1)\hat{\sigma}_n^2 + 2(\hat{\mu}_n - \hat{\mu}_{n+1}) \sum_{n+1} (x_i - \hat{\mu}_n)}{n} \\
&\quad + \frac{n \cdot (\hat{\mu}_n - \hat{\mu}_{n+1})^2 + (x_{n+1} - \hat{\mu}_n)^2 + (\hat{\mu}_n - \hat{\mu}_{n+1})^2}{n} \\
&= \frac{(n-1)\hat{\sigma}_n^2 + (x_{n+1} - \hat{\mu}_n)^2}{n} - \frac{n+1}{n} (\hat{\mu}_{n+1} - \hat{\mu}_n)^2.
\end{aligned} \tag{A.5}$$

Since for larger values of $n$, $(n+1)/n$ is 1, we finally write $\hat{\sigma}_{n+1}^2$ as

$$\hat{\sigma}_{n+1}^2 = \frac{(n-1)\hat{\sigma}_n^2 + (x_{n+1} - \hat{\mu}_n)^2}{n} - (\hat{\mu}_{n+1} - \hat{\mu}_n)^2. \tag{A.6}$$

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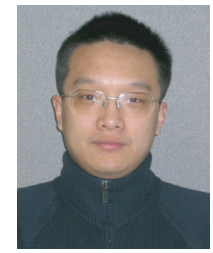
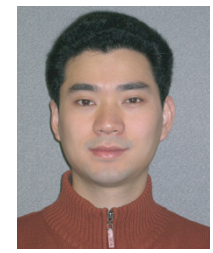



**Bian Wu** was born in Jiangxi, China in 1977. He received his B.S. degree in electrical engineering from Shanghai Tiedao University, Shanghai, China in 1999. He is currently pursuing the Ph.D. degree in pattern recognition and intelligent system from Shanghai Jiaotong University, Shanghai, China. Since 2001, he has also been a joint Ph.D. student in Motorola Labs China Research Center. His current research interests are speech recognition in noisy environments, adaptive speech signal processing, and multimedia system. He is now working with researchers and engineers at Motorola on the applications of speech recognition on embedded mobile devices.


**Xiaolin Ren** was born in 1973 in Zhejiang, China. He received his B.S. degree in 1994 in electronic engineering from Zhejiang University at Xiqi, Hangzhou, China, M.S. degree in 1997 in communications and electronic systems from Nanjing University of Science and Technology, Nanjing, China, and Ph.D. degree in 2000 in circuits and systems from Shanghai Jiaotong University, Shanghai, China, respectively. Since 2000 he has been with Motorola China Research Center, Shanghai, China. His research interests include nonlinear signal processing, speech processing, speech recognition, and applications of speech recognition in embedded systems such as mobile phones and PDAs.

**Chongqing Liu** received his B.S. degree in electrical engineering from Shanghai Jiaotong University, Shanghai, China, in 1961. He is a Professor of pattern recognition and intelligence system, and Director of the Pattern Recognition and Computer Vision Program. His principal interests are in digital information processing, pattern recognition, and computer vision. His current research activities include human face recognition, speech, and objects detection and tracking.

**Yaxin Zhang** graduated from Xidian University, Xi'an, China, in 1977. He was a Lecturer in a number of universities in China from 1977 to 1990. He received the Ph.D. degree in electronic engineering from the University of Western Australia in 1996. He worked for Motorola Australian Research Center from 1996 to 2000. Now he is a Distinguished Member of Technical Staff and the Senior Research Manager of speech recognition in Motorola China Research Center in Shanghai. His research interests include speech signal processing and automatic speech recognition.