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Research Article

Tracking Intermittently Speaking Multiple Speakers Using a Particle Filter

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The problem of tracking multiple intermittently speaking speakers is difficult as some distinct problems must be addressed. The number of active speakers must be estimated, these active speakers must be identified, and the locations of all speakers including inactive speakers must be tracked. In this paper we propose a method for tracking intermittently speaking multiple speakers using a particle filter. In the proposed algorithm the number of active speakers is firstly estimated based on the Exponential Fitting Test (EFT), a source number estimation technique which we have proposed. The locations of the speakers are then tracked using a particle filtering framework within which the decomposed likelihood is used in order to decouple the observed audio signal and associate each element of the decomposed signal with an active speaker. The tracking accuracy is then further improved by the inclusion of a silence region detection step and estimation of the noise-only covariance matrix. The method was evaluated using live recordings of 3 speakers and the results show that the method produces highly accurate tracking results.

1. Introduction

The ability to track the locations of intermittently speaking multiple speakers in the presence of background noise and reverberation is of great interest due to the vast number of potential applications. In the traditional approach to this problem, firstly the location of each speaker is estimated using a sound source localization method such as the MUSIC or time-delay of arrival (TDOA) methods, and then the estimated locations (contacts) are used as inputs to the tracking process using a Kalman filter or extended Kalman filter. In addition, in order to track multiple targets, a data association technique such as Joint Probability Data Association (JPDA) is exploited to bind each estimated location to a target [1].

Recently, the framework of Bayesian unified tracking has been applied to the multiple-target tracking problem [2]. In this framework, the location of a target is not explicitly estimated. Instead, the location estimation, data association, and tracking are simultaneously solved by combining an observation model with a motion model. Moreover, in this framework, a Kalman or extended Kalman filter is not used because the tracking process treats raw input signals from array sensors directly, instead of using the estimated contacts as inputs.

Under these circumstances particle filtering techniques are often applied, and in recent years, some authors have reported the application of these techniques to tracking audio sources, for example, [3, 4]. Using the particle filtering approach, the probability distribution of the estimated locations of the sources being tracked is approximated with a distribution of a state vector of particles and the state of each particle is recursively updated. The prediction step uses prior information about each source's previous location together with a predefined motion model (usually a random walk, which is a simple model and one that allows us to evaluate the performance of the particle algorithm itself), to predict the current locations of the sources. This "prediction-likelihood" is then weighted using received microphone signals, through the measurement likelihood, and particles are resampled according to their weights to obtain the posterior distribution from which the location estimate can be found.

The incorporation of any prior knowledge into this framework allows for more robust tracking as seen in [3], where the application of Time Delay Estimation (TDE) within a particle filtering framework provides improved robustness to spurious peaks in the correlation caused by reverberation and background noise. As well as this increased robustness the number of data samples required by particle filtering methods is less than that required for high resolution techniques such as MUSIC [5]. This is a particularly important point when tracking moving sources.

While various particle filtering methods have been applied to the problem of tracking a single speaker, the extension of these techniques to the case of multiple speakers is not straightforward. This is mainly due to the fact that one or more of the speakers may not be speaking at any given moment, making it necessary to estimate the number of "active" speakers and also which particular speakers are active at that time.

In the literature this problem is solved by introducing hidden variables which represent the status of each speaker. Then the particle filter is applied to solve the joint problem of estimating the speaker status and tracking the locations of speakers [6, 7]. However, this approach leads to greater computational complexity as the number of speakers increases. Therefore in this paper we instead use an alternative approach of firstly estimating the number of active speakers and then using the particle filter to perform the tracking of their locations.

In order to estimate the number of active speakers, we introduce a method based on the Exponential Fitting Test (EFT), a source number estimation technique proposed in [8] and which is extended to allow for the presence of reverberation in [9]. Identification of the active speakers is then performed. Finally, all speakers, including inactive speakers who are silent for some periods of time during the recording process are tracked using a particle filter.

It should be noted that once a speaker becomes inactive, he can no longer be tracked. However, using the state transition probability, an estimate of an inactive speaker location can be retained, which is an advantage in updating the speaker location once the speaker becomes active again. A block diagram for the proposed algorithm is shown in Figure 1. Live recordings are used, firstly, to evaluate the tracking algorithm and then, secondly, to evaluate the performance of the proposed speaker activity detection step.

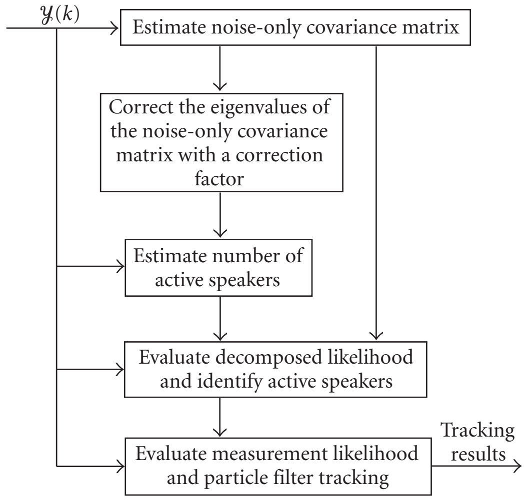


Figure 1: Block diagram for the proposed algorithm.

2. Problem Formulation

In this paper we investigate the problem of tracking the location of N_s moving speakers using an array of M microphones. Each speaker speaks intermittently. The audio signal is treated in the frequency domain. The short-time Fourier transform (STFT) of the M microphone inputs is denoted as

$$\mathbf{y}(\omega, t) = \left[y_1(\omega, t), \ldots, y_M(\omega, t)\right]^T, \tag{1}$$

where $y_m(\omega, t)$ denotes the STFT of the mth microphone input at time t and frequency ω, and the superscript T denotes the transpose of a vector or a matrix. We estimate the location of speakers every N STFT frames. A processing data block is denoted as

$$\mathbf{Y}(\omega, k) = [\mathbf{y}(\omega, t_0), \ldots, \mathbf{y}(\omega, t_0 + N - 1)], \tag{2}$$

where t_0 is the start time of the kth block.

Let $\mathcal{Y}(k)$ and $\Theta(k)$ denote the entire data in the kth block and the locations of the N_s speakers, respectively. That is

$$\begin{gathered}\mathcal{Y}(k) = \{\mathbf{Y}(\omega_{\min}, k), \ldots, \mathbf{Y}(\omega_{\max}, k)\}, \\ \Theta(k) = [\theta_1(k), \ldots, \theta_{N_s}(k)],\end{gathered} \tag{3}$$

where $\omega_{\min}$ and $\omega_{\max}$ are the lowest and highest frequencies respectively. Then our problem is to estimate $\Theta(k)$ using observed data $\mathcal{Y}_{1|k} = \{\mathcal{Y}(1), \ldots, \mathcal{Y}(k)\}$.

2.1. Bayesian Multiple Target Tracking. We treat the problem within the framework of Bayesian tracking theory [2]. In this framework, the tracking problem is reduced to calculating the posterior probability distribution $p(\Theta(k) \mid \mathcal{Y}_{1|k})$ of the target variable $\Theta(k)$ given the observation $\mathcal{Y}_{1|k}$. We introduce the standard Markov assumption about the movement of the speakers and the observation process. That is, we assume that the following recursive equation holds for all k:

$$\begin{aligned}p(\Theta(k) \mid \mathcal{Y}_{1|k}) = \frac{1}{Z}\ p(\mathcal{Y}(k) \mid \Theta(k)) \int p(\Theta(k) \mid \Theta(k-1)) \\ \times p(\Theta(k-1) \mid \mathcal{Y}_{1|k-1})\, d\,\Theta(k-1),\end{aligned} \tag{4}$$

where Z is the normalization constant, $p(\mathcal{Y}(k) \mid \Theta(k))$ is the measurement likelihood (observation model), and $p(\Theta(k) \mid \Theta(k-1))$ is the state transition probability (motion model).

2.2. Particle Filters. In general, computing the integral according to $\Theta(k-1)$ in (4) is analytically impossible for nonlinear observation/motion models. The usual numerical integration becomes intractable as the number of speakers N_s increases because the dimension of the integrated variable space increases and the computational cost increases exponentially. The particle filter is a popular approach to calculate the posterior distribution approximately for nonlinear models [10].

The posterior distribution of the target variable $\Theta(k)$ is approximated by the distribution of a number of weighted discrete points, that is, particles. The ith particle is associated with a state value of $\Theta^i(k)$ and a weight value w^i called "the importance" of the particle. Then the empirical probability density of Θ is defined as

$$p_{\text{emp}}(\Theta(k)) = \frac{1}{N_p}\sum_{i=1}^{N_p} w^i \delta\Big(\Theta(k) - \Theta^i(k)\Big), \tag{5}$$

where N_p is the number of particles and $\delta(x)$ is Dirac's delta function. If the particles are correctly distributed, then according to Kolmogorov's strong law of large numbers, as the number of particles increases toward infinity the empirical distribution approaches the true posterior density.

A recursive step of the simplest particle filtering algorithm for computing the posterior $p(\Theta(k) \mid \mathcal{Y}_{1|k})$ is as follows.

(1) Let a set of particles and weights for the $k-1$th block $\{\Theta^i(k-1), w^i(k-1), i = 1, \dots, N_p\}$ be given.

(2) Generate a new set of particles $\{\Theta^i(k)\}$ by propagating the particles according to the motion model $p(\Theta(k) \mid \Theta(k-1))$.

(3) Compute the measurement likelihood $p(\mathcal{Y}(k) \mid \Theta^i(k))$ for each particle.

(4) Revise the weight values as $w^i(k) = p(\mathcal{Y}(k) \mid \Theta^i(k))w^i(k-1)$ and normalize the weights as $\sum_i w^i(k) = 1$.

(5) Resample particles in proportion to the weight values and reset all weights as $1/N_p$.

Hence, for implementing the basic particle filter, only the evaluation of the measurement likelihood for each particle is necessary.

The final estimate of the source locations can then be obtained by maximizing the posterior probability distribution (MAP estimate), or by taking the weighted mean over the particles as

$$\widehat{\Theta(k)} = \frac{1}{N_p}\sum_{i=1}^{N_p} w^i \Theta^i(k). \tag{6}$$

This yields an approximation of the expectation of $\Theta(k)$ under the posterior $p(\Theta(k) \mid \mathcal{Y}_{1|k})$, which is called the minimum mean-square error (MMSE) estimate. In this research, we used the MMSE estimate.

2.3. The Problem of Intermittent Speech. So far we have explained the standard procedure for Bayesian multiple target tracking. The main difficulty with our problem comes from the fact that speakers speak intermittently. This means that the measurement likelihood $p(\mathcal{Y}(k) \mid \Theta(k))$ changes depending on the status of each speaker, that is, which speakers are active in the kth block.

In previous studies this problem has been solved by introducing hidden variables which represent the status of each speaker. Then a particle filter is applied to solve the joint problem of estimating the speaker status and tracking the locations of speakers [6, 7]. However this approach turns out to require large numbers of particles when the number of speakers increases, in order to estimate the active speakers using a particle filter, because the number of possible combinations of active and inactive speakers increases exponentially. This property is not suitable for real-time applications.

In this paper we instead propose an alternative approach of firstly estimating the number of active speakers and identifying them, then using a particle filter to perform the tracking. With this approach, the particle filter is not used to track the combinatorial speakers' status and the number of particles can be reduced. In addition, we introduce online estimation of the noise covariance matrix based on detection of the silence region (for details of the detection method, see Section 3.2). Figure 1 depicts a block diagram of the overall tracking process. Each step is explained in detail in the following sections.

3. Noise-Only Covariance Estimation

As the first step, the noise-only frequency subbands are identified by a pause detection technique, and the noise-only covariance matrix is estimated. In order to determine the number of speakers, we need the eigenvalues of the noise-plus-reverberation matrix. However, this matrix is unknown. Instead, since we can estimate the noise-only covariance matrix, we consider obtaining a better approximation to the true noise-plus-reverberation eigenvalues by correcting the eigenvalues of the noise-only covariance matrix with a correction factor. The correction factor is discussed in Section 4. Therefore, in this section, we propose a method for estimating the noise-only covariance matrix.

3.1. Signal Model. We denote the number of active speakers by N_a. The microphone input $\mathbf{y}(\omega, t)$ for N_a directional signals $\mathbf{s}(\omega, t)$ plus background noise $\mathbf{n}(\omega, t)$ is modeled as

$$\mathbf{y}(\omega, t) = \mathbf{A}(\omega, k)\mathbf{s}(\omega, t) + \mathbf{n}(\omega, t), \tag{7}$$

where $\mathbf{A}(\omega, k)$ is the matrix composed of the N_a direct path transfer function vectors:

$$\mathbf{A}(\omega, k) = \left[\mathbf{a}_1(\omega, k), \dots, \mathbf{a}_{N_a}(\omega, k)\right]. \tag{8}$$

Here we assume that $\mathbf{A}$ is constant during a processing data block, that is, $\mathbf{A}$ depends only on k. This assumption is satisfied when N, the size of the processing block, is small enough. In the experiment below, we set N equal to 9; this means that the block length is 0.1 second, where the time 0.1 second is derived from the experimental conditions shown in Table 1 in Section 6. Each transfer function vector is

$$\mathbf{a}_l(\omega, k) = \left[e^{-j\omega\tau_{1l}(k)}a_{1l}(k), \dots, e^{-j\omega\tau_{Ml}(k)}a_{Ml}(k)\right], \quad (9)$$

where $a_{ml}(k)$ and $\tau_{ml}(k)$ denote the gain and the time delay, respectively, between the lth speaker and the mth microphone. $\mathbf{s}(\omega, t) = [s_1(\omega, t), \dots, s_{N_a}(\omega, t)]^T$ is the source spectrum vector, and $\mathbf{n}(\omega, t) = [n_1(\omega, t), \dots, n_M(\omega, t)]^T$ is the background noise spectrum vector.

Normally it is assumed that the signal and noise are uncorrelated and that the noise is Gaussian with known power. However, in most practical situations this assumption will not hold because of the existence of reverberation, and it is shown in [11] that it leads to degraded tracking results. It is therefore desirable to use a more accurate model of the background noise.

3.2. Determination of Silence Regions of Speakers. We first detect the noise-only subbands based on the noise characterization method proposed in [12], in which a threshold is applied to each frequency subband in order to distinguish between frequencies containing only noise and frequencies containing speech components.The energy of a subband ω for the kth block is defined as

$$E(\omega, k) = \frac{1}{N}\sum_{t=t_0}^{t_0+N-1} \mathbf{y}(\omega, t)^H \mathbf{y}(\omega, t), \quad (10)$$

where the superscript H denotes the conjugate transpose of the matrix. The noise threshold $\eta(\omega, k)$ is calculated as

$$\eta(\omega, k) = \beta E_n(\omega, k-1), \quad (11)$$

where β is a constant value lying between 1.5 and 2.5 which can be chosen during the training period. $E_n(\omega, k-1)$ is the energy of the previous noise estimate at the given frequency ω and it is determined by averaging the previous noise energy values at this frequency over a specified time period.

A decision is then made as to whether or not each frequency subband contains the required target signal. If the power of the subband $E(\omega, k)$ satisfies $E(\omega, k) \le \eta(\omega, k)$, the frequency value ω is determined as a noise-only subband and $E_n(\omega, k)$ is updated using $E(\omega, k)$. Otherwise, ω is considered to contain signal components, and $E_n(\omega, k)$ is not updated ($E_n(\omega, k) = E_n(\omega, k-1)$). This allows the noise power estimate to be continuously updated on a frequency-by-frequency basis, even while someone is speaking.

3.3. Calculate Noise-Only Covariance Matrix. The noise-only covariance matrix estimate for a frequency subband ω can be defined as

$$\mathbf{C}_n(\omega, k) = \frac{1}{N}\sum_{t=t_0}^{t_0+N-1} \mathbf{n}(\omega, t)\mathbf{n}^H(\omega, t). \quad (12)$$

If $E(\omega, k) < \eta(\omega, k)$, the frequency subband is determined to contain no signal component. This means that $\mathbf{y}(\omega, t) = \mathbf{n}(\omega, t)$ and the estimate of the covariance can be computed as

$$\mathbf{C}_n = \frac{1}{N}\sum_{t=t_0}^{t_0+N-1} \mathbf{y}(\omega, t)\mathbf{y}^H(\omega, t). \quad (13)$$

The resulting covariance estimate is then smoothed over some period of time in order to stabilize the estimate

$$\widetilde{\mathbf{C}}_n(\omega, k) = \frac{1}{Q}\sum_{q=k-Q+1}^{k} \mathbf{C}_n(\omega, q), \quad (14)$$

where Q is the number of previous values used for smoothing.

4. Estimation of the Number of Active Speakers

The second step is estimating the number of active speakers N_a. For sound source number estimation, statistical model selection criteria such as the Minimum Description Length (MDL) [13] and Akaike's Information Criterion (AIC) [14] are traditionally used. However, both these approaches are based on an assumption of white noise and are known to consistently overestimate the number of sources present when reverberation is present [15].

In what follows we use the method proposed in [8], extended to cover reverberant environments as detailed in [9]. The method is based on analyzing the eigenvalues of the covariance matrix of input signals. Hereinafter, we describe the procedure for a frequency subband ω in a processing block k. The index of the block k and the index of the subband frequency ω are omitted for the sake of simplicity where they are unnecessary.

The spatial correlation matrix $\mathbf{K}_y$ of the received signals is defined as

$$\mathbf{K}_y = E\left[\mathbf{y}(t)\mathbf{y}^H(t)\right], \quad (15)$$

where $E[\cdots]$ denotes taking the average over time. Using the signal model (7), the covariance can be written as

$$\mathbf{K}_y = \mathbf{A}\mathbf{K}_s\mathbf{A}^H + \mathbf{K}_n, \quad (16)$$

where

$$\begin{aligned}\mathbf{K}_s &= E\left[\mathbf{s}(t)\mathbf{s}^H(t)\right], \\ \mathbf{K}_n &= E\left[\mathbf{n}(t)\mathbf{n}^H(t)\right].\end{aligned} \quad (17)$$

As is described in the previous section, normally it is assumed that the signal and the noise are uncorrelated. Then the covariance matrices become

$$\mathbf{K}_s = \operatorname{diag}\{\gamma_1, \dots, \gamma_{N_a}\}. \quad (18)$$

Here, diag $\{\cdots\}$ denotes a diagonal matrix with diagonal elements $\{\cdots\}$ and γ_l denotes the power of $s_l(t)$, that is, $\gamma_l = E[s_l(t)s_l^*(t)]$, where the superscript * represents the conjugate. In the same manner, the observed noise is assumed to be uncorrelated:

$$\mathbf{K}_n = \operatorname{diag}\{\sigma_1^2, \ldots, \sigma_M^2\}, \tag{19}$$

where σ_i^2 $(i = 1, \ldots, M)$ denotes the power of $n_i(t)$.

If we can assume that all σ_i^2 are equal to σ^2, the noise covariance can be written as $\mathbf{K}_n = \sigma^2\mathbf{I}$ using the $M \times M$ identity matrix $\mathbf{I}$. Then (16) can be reexpressed as:

$$\mathbf{K}_y = \mathbf{A}\mathbf{K}_s\mathbf{A}^H + \sigma^2\mathbf{I}, \tag{20}$$

and the eigenvalues of $\mathbf{K}_y$ are therefore given by

$$\lambda_1, \ldots, \lambda_M = \gamma_1 + \sigma^2, \ldots, \gamma_{N_a} + \sigma^2, \sigma^2, \ldots, \sigma^2. \tag{21}$$

The number of eigenvalues corresponding to the signal subspace, the so-called signal eigenvalues, is equal to the number of active sources, and assuming that the source power is greater than that of the background noise, the number of sources present can now be easily determined as the number of eigenvalues not equal to σ^2.

In practice, however, $\mathbf{K}_y$ is unknown and must instead be estimated using

$$\mathbf{C}_y = \frac{1}{N}\sum_{t=t_0}^{t_0+N-1} \mathbf{y}(t)\mathbf{y}^H(t). \tag{22}$$

In this case the active source number estimation problem still consists of distinguishing between the signal and noise eigenvalues. However, with the statistical fluctuations in $\mathbf{C}_y$, the noise eigenvalues are no longer all equal to σ^2. In particular, for moving sources, we cannot take large N and the fluctuations become larger. The separation between noise and signal eigenvalues is only clear now in the case of high Signal-to-Noise Ratio (SNR) and low reverberation, when a gap can be clearly observed.

In order to distinguish between signal and noise eigenvalues for moving sources conditions, we approximate the decreasing profile of the eigenvalues of the noise spatial correlation matrix $\widetilde{\mathbf{C}}_n$, and compare this to the profile of the observed eigenvalues of $\mathbf{C}_y$. It is known that a decreasing profile can be approximated using the first- and second-order moments of the eigenvalues together with an initial assumption of white noise [8]. The smallest observed eigenvalue λ_M is assumed to be a noise eigenvalue, corresponding to a noise subspace dimension of $d = 1$. Then incrementing d by 1 for each subsequent step until $d = M - 1$, the predicted profile of the noise only eigenvalues is found recursively using

$$\hat{\lambda}_{M-d} = (d+1)J_{d+1}\hat{\sigma}^2 \tag{23}$$

where

$$J_{P+1} = \frac{1 - r_{d+1,N}}{1 - (r_{d+1,N})^{d+1}},$$

$$\hat{\sigma}^2 = \frac{1}{d+1}\sum_{i=0}^{d}\lambda_{M-i}, \tag{24}$$

$$r_{m,n} = e^{-2\xi_{m,n}},$$

$$\xi_{m,n} = \sqrt{\frac{1}{2}\left\{\frac{15}{m^2+2} - \sqrt{\frac{225}{(m^2+2)^2} - \frac{180m}{n(m^2-1)(m^2+2)}}\right\}}. \tag{25}$$

The relative differences between the predicted and observed mth eigenvalue profiles δ_m are calculated using

$$\delta_m = \frac{\lambda_m - \hat{\lambda}_m}{\hat{\lambda}_m}, \quad m = 1, \ldots, M-1, \tag{26}$$

and δ_m is then compared to a threshold value η_m in order to distinguish the signal eigenvalues. These threshold values η_m for $m = 1, 2, \ldots, M-1$ are selected from the distribution of the relative differences for each frequency component when there is only noise present at that frequency (for a discussion on how to select this threshold value see [9]). Also, for the details on the derivation of (23) through (25), see [8].

The predicted noise eigenvalue profile $\hat{\lambda}_1, \ldots, \hat{\lambda}_M$ is based on the assumption that the background noise can be modeled as white noise. This approximation is valid in many practical situations when none of the speakers are active. Once some of the speakers are active though, reverberant tails arising due to the presence of speech violate this white noise assumption and lead to an increase in the noise eigenvalue profile.

In this case the noise eigenvalue profile predicted from (23)–(25) will be lower than that of the observed noise eigenvalues, resulting in frequent overestimation of the number of active sources. Therefore once it is known that at least one speaker is present, it is necessary to apply a correction factor to the predicted profile in order to account for the increase in the noise eigenvalues due to reverberation.

In order to calculate a suitable correction factor the eigenvalues of the estimated reverberation-only correlation matrix, $\lambda_1^{\text{rev}}, \ldots, \lambda_M^{\text{rev}}$, are evaluated. These values are then used to find the corresponding predicted noise eigenvalues $\hat{\lambda}_1^{\text{rev}}, \ldots, \hat{\lambda}_M^{\text{rev}}$ as described in (23)–(25). It should be noted that the reverberation-only correlation matrix is estimated using impulse responses recorded in the room in which the tracking is carried out.

The difference between the predicted and observed profiles, relative to the largest observed eigenvalue, is then taken as a correction factor:

$$cf_m = \frac{\lambda_m^{\text{rev}} - \hat{\lambda}_m^{\text{rev}}}{\lambda_1^{\text{rev}}}, \quad m = 2, \ldots, M. \tag{27}$$

In the presence of at least one active source the correction factor is then used to modify the originally predicted noise eigenvalue profile:

$$\hat{\lambda}_m^{\text{mod}} = \hat{\lambda}_m + cf_m\lambda_1. \tag{28}$$

Once again the predicted and observed profiles are compared by finding their relative difference:

$$\delta_m^{\text{mod}} = \frac{\lambda_m - \hat{\lambda}_m^{\text{mod}}}{\hat{\lambda}_m^{\text{mod}}}. \tag{29}$$

If $\delta_m^{\text{mod}} > \eta_m$ then λ_m is a signal eigenvalue. The number of active speakers at this subband is then estimated as the number of signal eigenvalues. In order to obtain the final estimate of the number of active speakers for the broad band signal, $\widehat{N_a}$, the estimate in each subband is averaged over all active subbands within the frequency range $[\omega_{\min}, \omega_{\max}]$.

5. Evaluating Measurement Likelihood

The third step is identifying the active speakers and evaluating the measurement likelihood $p(\mathcal{Y} \mid \Theta^i)$ for each particle. We exploit the random signal model in [16], that is, we assume that each $\mathbf{s}(t)$ is a 0-mean circular complex Gaussian random vector, with unknown covariance, and that successive samples of $\mathbf{s}(t)$ are independent but share a common density. We also assume that components of $\mathbf{s}(t)$ are independent of each other; hence the covariance matrix $\mathbf{K}_s$ is diagonal.

5.1. Decomposing the Likelihood. For a while, we assume that all N_s speakers are speaking. Then the log likelihood function of the observed data $\mathbf{Y}(\omega)$ given the location of the N_s speakers Θ, the signal covariance matrix $\mathbf{K}_s(\omega)$, and the noise covariance matrix $\mathbf{K}_n(\omega)$ is

$$\begin{aligned} L_y(\mathbf{Y} \mid \Theta, \mathbf{K}_s, \mathbf{K}_n) &= -N \log\left|\det\left(\mathbf{K}_y\right)\right| \\ &\quad - \frac{1}{2}\sum_{t=t_0}^{t_0+N-1} \mathbf{y}^H(t)\mathbf{K}_y^{-1}\mathbf{y}(t), \end{aligned} \tag{30}$$

where we have discarded unnecessary constant terms. As we described, $\mathbf{K}_y$ can be written as

$$\mathbf{K}_y = \mathbf{A}(\Theta)\mathbf{K}_s\mathbf{A}(\Theta)^H + \mathbf{K}_n, \tag{31}$$

where

$$\mathbf{A}(\Theta) = \left[\mathbf{a}(\theta_1), \ldots, \mathbf{a}(\theta_{N_s})\right], \tag{32}$$

and $\mathbf{a}(\theta_l)$ is the transfer function vector for the location θ_l. Note that the log likelihood function L_y is a nonlinear function of the location parameters Θ. Hence, it is impossible to apply the Kalman filter to our tracking problem.

Now we introduce a hidden "complete data vector" $\mathbf{x}(t) = [\mathbf{x}_1^T(t), \ldots, \mathbf{x}_{N_s}^T(t)]$ as in [16] which corresponds to the signal due to each speaker, and assume that the observed microphone signals can be decomposed into these signals as

$$\mathbf{y}(t) = \sum_{l=1}^{N_s} \mathbf{x}_l(t) = \mathbf{H}\mathbf{x}(t), \tag{33}$$

where

$$\begin{aligned} \mathbf{x}_l(t) &= \mathbf{a}(\theta_l)\mathbf{s}_l(t) + \mathbf{n}_l(t), \\ \mathbf{H} &= [\mathbf{I}, \ldots, \mathbf{I}], \end{aligned} \tag{34}$$

where $\mathbf{n}_l(t)$ is an arbitrary decomposition of the noise vector $\mathbf{n}(t)$, which must satisfy $\sum_{l=1}^{N_s} \mathbf{n}_l(t) = \mathbf{n}(t)$.

Then under the assumption of uncorrelated signals, that is,

$$\mathbf{K}_s = \operatorname{diag}\{\gamma_1, \ldots, \gamma_{N_s}\}, \tag{35}$$

the log likelihood of $\mathbf{Y}$ can be decomposed into the sum of the log likelihoods of the individual $\mathbf{X}_l = [\mathbf{x}_l(t_0), \ldots, \mathbf{x}_l(t_0 + N - 1)]$ thus

$$L_y(\mathbf{Y} \mid \Theta, \mathbf{K}_s, \mathbf{K}_n) = \sum_{l=1}^{N_s} L_{xl}(\mathbf{X}_l \mid \theta_l, \gamma_l, \mathbf{K}_{nl}). \tag{36}$$

Here

$$\begin{aligned} L_{xl}(\mathbf{X}_l \mid \theta_l, \gamma_l, \mathbf{K}_{nl}) &= -N \log|\det(\mathbf{K}_{xl})| \\ &\quad - \frac{1}{2}\sum_{t=t_0}^{t_0+N-1} \mathbf{x}_l^H(t)\mathbf{K}_{xl}^{-1}\mathbf{x}_l(t), \end{aligned} \tag{37}$$

$$\begin{aligned} \mathbf{K}_{xl} &= \gamma_l \mathbf{a}(\theta_l)\mathbf{a}^H(\theta_l) + \mathbf{K}_{nl}, \\ \mathbf{K}_{nl} &= E\left[\mathbf{n}_l(t)\mathbf{n}_l^H(t)\right]. \end{aligned} \tag{38}$$

Using the sample covariance matrix $\mathbf{C}_{xl}$ of the complete data $\mathbf{X}_l$

$$\mathbf{C}_{xl} = \frac{1}{N}\sum_{t=t_0}^{t_0+N-1} \mathbf{x}_l(t)\mathbf{x}_l^H(t), \tag{39}$$

the log-likelihood can be rewritten as:

$$\begin{aligned} L_{xl}(\mathbf{X}_l \mid \theta_l, \gamma_l, \mathbf{K}_{nl}) &= -N \log|\det(\mathbf{K}_{xl})| \\ &\quad - \frac{N}{2}\operatorname{tr}\left[\mathbf{C}_{xl}\mathbf{K}_{xl}^{-1}\right]. \end{aligned} \tag{40}$$

As the complete data is not known $\mathbf{C}_{xl}$ cannot be determined directly. However the correlation matrix can be estimated using the following equations in the Expectation step of the EM algorithm in [16]:

$$\begin{aligned} \mathbf{C}_{xl} &= E\left[\mathbf{C}_{xl} \mid \mathbf{C}_y; \widehat{\mathbf{K}}_y\right] \\ &= \widehat{\mathbf{K}}_{xl} - \widehat{\mathbf{K}}_{xl}\widehat{\mathbf{K}}_y^{-1}\widehat{\mathbf{K}}_{xl} + \widehat{\mathbf{K}}_{xl}\widehat{\mathbf{K}}_y^{-1}\mathbf{C}_y\widehat{\mathbf{K}}_y^{-1}\widehat{\mathbf{K}}_{xl}, \end{aligned} \tag{41}$$

with

$$\begin{aligned} \widehat{\mathbf{K}}_y &= \sum_{l=1}^{N_s} \widehat{\mathbf{K}}_{xl}, \\ \widehat{\mathbf{K}}_{xl} &= \widehat{\gamma}_l \mathbf{a}(\theta_l)\mathbf{a}^H(\theta_l) + \mathbf{C}_{nl}. \end{aligned} \tag{42}$$

It can be seen that this expression requires $\widehat{\gamma}_l$, an estimation of the power of the lth speaker, and $\mathbf{C}_{nl}$, an estimation of the decomposed noise covariance matrix $\mathbf{K}_{nl}$. γ_l can be estimated from θ_l using

$$\widehat{\gamma}_l = \frac{\mathbf{a}^H(\theta_l)\mathbf{C}_y\mathbf{a}(\theta_l)}{\mid \mathbf{a}(\theta_l)\mid^4}. \tag{43}$$

Table 1: Experimental parameters.

Sampling frequency	16000 Hz
FFT length	512
FFT shift	128
Frequency range	230–800 Hz
Block length N	9 (0.1 s)
Q	25 s
N_p	100
β	1.5

Finally the estimate of the decomposed noise covariance matrix $\mathbf{C}_{nl}$ is given by evenly dividing the noise-only-reverberant covariance matrix, which is estimated in Section 3.3, among the number of speakers as:

$$\mathbf{C}_{nl} = \frac{1}{N_s}\tilde{\mathbf{C}}_n. \quad (44)$$

This method allows for tracking the sources in situations where there is no prior knowledge of the background noise, thus making it much more useful for practical tracking problems.

Applying the above procedure for all active frequency subbands ω and taking the mean of $L_{xl}(\mathbf{X}_l(\omega) \mid \theta_l, \hat{\gamma}_l(\omega), \mathbf{C}_{nl}(\omega))$, we get the estimated partial log likelihood $\hat{L}_{xl}(\mathcal{X}_l \mid \theta_l)$ as

$$\hat{L}_{xl}(\mathcal{X}_l \mid \theta_l) = \frac{1}{\mid \Omega_a \mid}\sum_{\omega\in\Omega_a} L_{xl}(\mathbf{X}_l(\omega) \mid \theta_l, \hat{\gamma}_l(\omega), \mathbf{C}_{nl}(\omega)), \quad (45)$$

where Ω_a and $\mid \Omega_a \mid$ are the set of active frequency subbands and the number of active subbands respectively, and $\mathcal{X}_l$ is the collection of $\mathbf{X}_l(\omega)$ for all active subbands.

5.2. Identifying Active Speakers. So far we have assumed that all N_s speakers are active. When one or more speakers are inactive, we need to identify the active speakers. In this paper we identify the active speakers by comparing the values of the estimated partial likelihood $\hat{L}_{xl}$ for the lth speaker.

We calculate the average of $\hat{L}_{xl}(\mathcal{X}_l \mid \theta_l^i)$ for all particles as

$$\overline{L}_{xl} = \frac{1}{N_p}\sum_{i=1}^{N_p}\hat{L}_{xl}\left(\mathcal{X}_l \mid \theta_l^i\right), \quad (46)$$

where θ_l^i is the lth value of the state vector of the ith particle. Then the lth speaker which corresponds to the $\widehat{N_a}$ largest values of (46) is determined to be active. Here $\widehat{N_a}$ is the estimate of the number of active speakers for the broad band signal which was given in Section 4. We denote the set of indices for the active speakers as $\mathcal{A}$.

5.3. Evaluating Likelihood. As the measurement likelihood of the audio input is irrelevant for the location of inactive speakers, the total log likelihood for the ith particle can be obtained by taking the sum of the decomposed log likelihoods only for active speakers as

$$\hat{L}_y\left(\mathcal{Y} \mid \Theta^i\right) = \sum_{l\in\mathcal{A}}\hat{L}_{xl}\left(\mathcal{X}_l \mid \theta_l^i\right). \quad (47)$$

Then the measurement likelihood for the ith particle is obtained as

$$p\left(\mathcal{Y} \mid \Theta^i\right) = \exp\left\{\hat{L}_y\left(\mathcal{Y} \mid \Theta^i\right)\right\}. \quad (48)$$

Using this likelihood, we can execute the particle filtering algorithm described in Section 2.2, and compute the estimate of the source location for the target processing block using the (6).

6. Experimental Results

The proposed tracking method was tested using recordings taken in a medium sized meeting room (585 m × 885 m) with a reverberation time of 500 millisecond. As shown in Figure 2, three people, one female and two males, moved around the room, while speaking intermittently. The speech was recorded using a uniform circular array of 8 microphones which was placed at ceiling height, and the distance between the microphone array and the speakers was sufficient to ensure far-field conditions. The recorded signals were divided into frames of length 32 millisecond, with an averaging interval of $N = 9$ (block length), or approximately 0.1 second. The experimental parameters are given in Table 1.

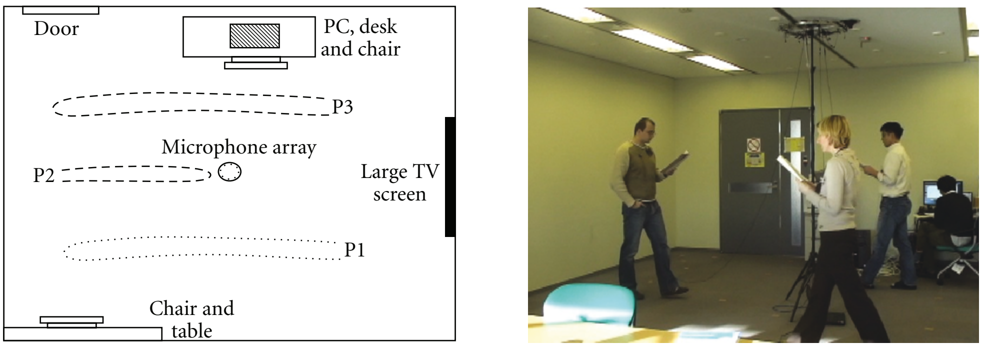
We note that the rates of the time intervals for the cases when only one speaker, two speakers, and three speakers are speaking are 15.6%, 48.3%, and 31.7%, respectively. The time intervals for the case when no speaker is active is only 4.4%. This means that the time during which multiple speakers are speaking simultaneously is rather long in the data. Moreover, the average times of a silence (inactive) region for speakers P1, P2, and P3 are 0.48 second, 0.26 second, and 0.93 second, respectively.

The true trajectory of the speakers was found using a zone positioning system ZPS-3D by Furukawa Co., Ltd. and is depicted by the dashed lines in Figure 2(a) and Figures 3, 4, and 5, which shows the experimental layout. Using the zone positioning system, a badge is pinned on the chest of each of the speakers and the location of the badge is then tracked. According to the specification of the system, the measurement accuracy is 20 to 80 mm depending on the environment and the measured distance.

In the following subsections we will describe the results of three experiments using the data. In Section 6.1 the accuracy of the proposed tracking method is evaluated using the Root Mean Square Error (RMSE) between the true trajectory and the estimated trajectory. Three kinds of noise covariance matrix, simply assuming white noise, using an estimate of the noise covariance matrix, and using modified noise covariance, are tested and compared. In Section 6.2, tracking results using two pseudolikelihood functions instead of (40) are shown for comparison purposes. In Section 6.3, the accuracy of the speech event detection by the proposed active

Table 2: Root Mean Square Error (RMSE) values for the case where the active speakers are estimated, where the RMSE values are calculated from distance estimation in meters (m). The headings "Total" and "Active" denote the error for the entire tracking time and for the time that each speaker was determined to be active, respectively.

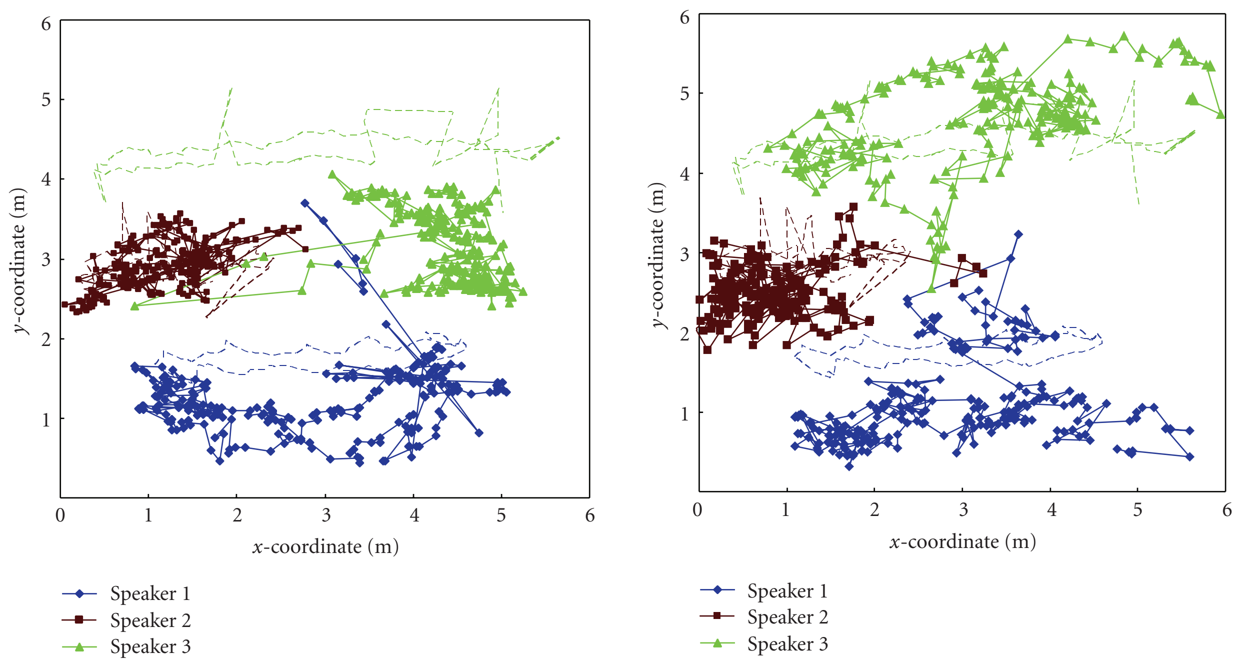
	White noise RMSE		Estimated noise RMSE	
Error	Total (m)	Active (m)	Total (m)	Active (m)
Speaker 1	0.78	0.51	1.11	0.78
Speaker 2	0.80	0.61	1.02	0.74
Speaker 3	2.0	1.16	1.06	0.61
Average over 3 speakers	**1.19**	**0.76**	**1.06**	**0.71**



(a) The three people are denoted P1, P2, P3, and the dashed line traces their movements. The microphone array is set at ceiling height

(b) Video image taken during recordings

Figure 2: Experimental layout.



(a) Measurement likelihood found using the proposed algorithm, Background noise assumed white.

(b) Measurement likelihood found using the proposed algorithm, Estimated background noise.

Figure 3: Tracking results. The dashed lines represent the trace of the actual motions.

TABLE 3: RMSE values for the case where all the diagonal elements of $\mathbf{C}_{\mathrm{nl}}$ are the same constant value, where the RMSE values are calculated from distance estimation in meters (m).

	RMSE	
Error	Total (m)	Active (m)
Speaker 1	0.76	0.50
Speaker 2	0.90	0.68
Speaker 3	1.21	0.67
Average over 3 speakers	**0.96**	**0.62**

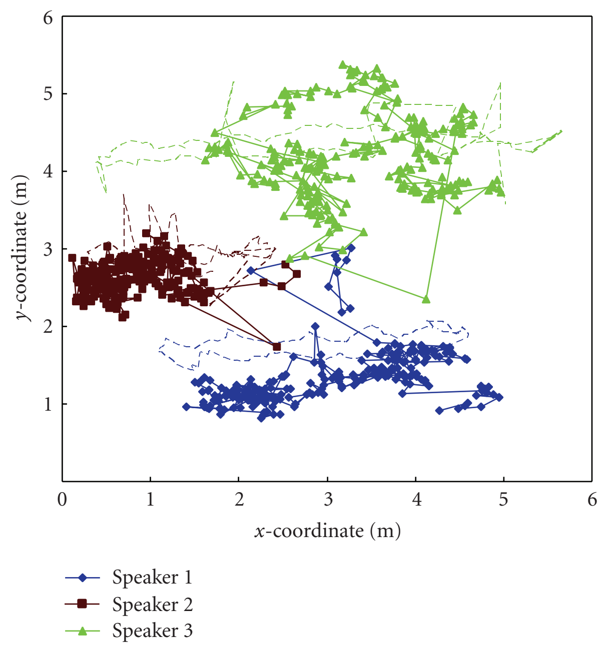


FIGURE 4: The tracking result (estimated covariance matrix of background noise, but the diagonal elements of the matrix are a constant value). The dashed lines represent the trace of the actual motions.

speaker identification step is evaluated because one of the main applications of the proposed method is envisaged as preprocessing for speech recognition.

6.1. Tracking Experiments. We will show the results when the number of active speakers is estimated at each time step and the silence region detection step is included to eliminate the noise only frequencies. The results for this case are shown in Figure 3, and the corresponding Root Mean Square Error (RMSE) values are shown in Table 2.

Figure 3(a) shows the case where the measurement likelihood is calculated using (48) and the background noise is assumed white. Figure 3(b) shows the result when the measurement likelihood is calculated using (48) and the noise covariance is estimated from the received data using (14) and (44).

An inactive speaker location can no longer be tracked, but using the state transition probability, an estimate of an inactive speaker location can be kept, which is an advantage in updating the speaker location, once the speaker becomes active again. Therefore, the location estimates of the inactive speakers cannot be expected to be very accurate. For this reason we demonstrate the RMSE values for both the entire data (total) and the time intervals that each speaker was determined to be active(active) in Table 2.

From Table 2, the average performance for the estimated noise case is better than that for the white noise case. This is because the performance of tracking Speaker 3 is improved by estimating the noise covariance matrix, $\mathbf{C}_{nl}$. However, the performances of tracking Speakers 1 and 2 for the estimated noise case became worse than those for the white noise case.

As a method of improving the result, we tried changing all the diagonal elements of $\mathbf{C}_{nl}$ to the same constant value (say, 0.1). The tracking result is shown in Figure 4 and the RMSE values are shown in Table 3. From the figure and table, one can see that the performances of tracking Speakers 1 and 2 are close to those for the white noise case and the performance of tracking Speaker 3 is close to that for the case of estimated noise.

From all the results, we conclude that the tracking performance is improved by estimating $\mathbf{C}_{nl}$, but that if the performance is not improved, it would be advisable to change all the diagonal elements of $\mathbf{C}_{nl}$ to the same constant value. It should be noted that the nondiagonal elements of $\mathbf{C}_{nl}$ are unchanged.

6.2. Other Likelihood Functions. For comparison purposes we then considered the same situation but this time the power spectrum as calculated using MUSIC and the energy from TDOA [17], as calculated using R_τ in (49), were instead used as a pseudolikelihood function for the current tracking method:

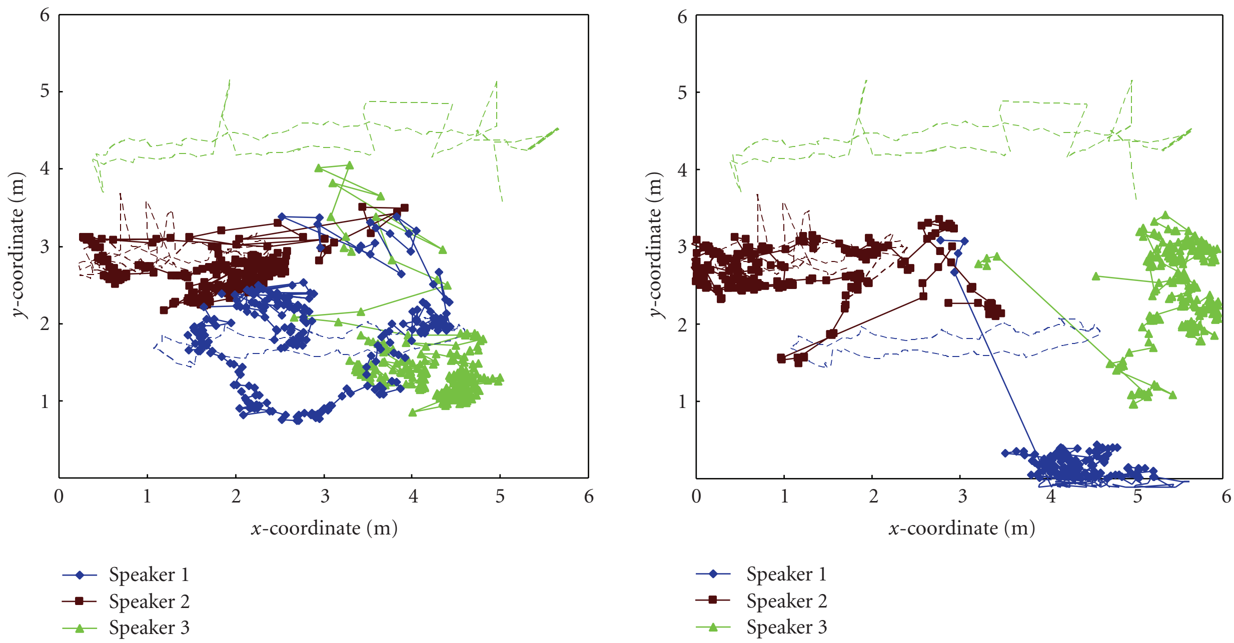
$$R_\tau = \sum_{i=1}^{M}\sum_{j=i+1}^{M} R_{ij}\left(\hat{\tau}_{ij}\right),$$
$$R_{ij}(\tau) = \frac{1}{N_{fl}}\sum_{k=0}^{N_{fl}-1}\frac{y_i(\omega_k)y_j^*(\omega_k)}{\mid y_i(\omega_k)y_j^*(\omega_k)\mid}e^{j\omega_k\tau}, \tag{49}$$

where $\hat{\tau}_{ij} = \max_\tau R_{ij}(\tau)$ and $\omega_k = 2\pi k/N_{fl}$.

Figures 5(a) and 5(b) show the results obtained by using MUSIC and TDOA, respectively. Table 4 shows the RMSE values of the results. From the results in Figures 5(a) and 5(b), MUSIC and TDOA can track at most, respectively, two speakers and one speaker. This might be because the power spectrum of MUSIC and the energy of TDOA are calculated detecting all speakers. Namely, the observations $\mathbf{y}(\omega, t)$, which include the information on all speakers, are used to calculate the likelihood function. On the other hand, the likelihood function of the proposed method is calculated for each speaker, using $\mathbf{x}_l(t)$ in (34) which includes the information on each active speaker. Therefore we conclude that the proposed method using (48) is more suitable for tracking multiple speakers. Note that we are able to confirm that, even if the number of speakers is four, the proposed method can track each speaker [18].

Table 4: RMSE values for the results obtained by MUSIC and TDOA, where the RMSE values are calculated from distance estimation in meters (m).

	MUSIC RMSE		TDOA RMSE	
Error	Total (m)	Active (m)	Total (m)	Active (m)
Speaker 1	1.31	0.92	2.46	1.81
Speaker 2	1.11	0.81	1.87	1.41
Speaker 3	2.59	1.56	2.88	1.79
Average Over 3 Speakers	**1.67**	**1.10**	**2.40**	**1.67**



(a) Measurement likelihood found using MUSIC

(b) Measurement likelihood found using TDOA

Figure 5: Tracking results. The dashed lines represent the trace of the actual motions.

Table 5: Speaker activity detection results.

	Speaker 1%	Speaker 2%	Speaker 3%	Average %
Speaker state correctly detected	73.11	58.09	50.29	60.50
Speaker incorrectly determined active	19.83	15.19	20.10	14.38
Speaker incorrectly determined inactive	7.05	26.72	29.63	21.13

6.3. Speech Event Detection. In this subsection, the performance of the active speaker identification step is investigated. While the recording in the experiment was being carried out, a lapel microphone was attached to each speaker so that the true period of each speech event could be hand labeled by human listeners. This labeling was then compared to the results found by the proposed active speaker identification method.

From the results given in Table 5 it can be seen that the mean rate of correct determination of the activity state is approximately 60%, with Speaker 3 having the lowest correct determination rate of 50.29%. However, since the incorrect determined active rate is low, we consider that the proposed active speaker identification method works well. Regarding the incorrectly determined inactive speakers, from the analysis of the speech segments, it turned out that there exists a situation where the speech volume is low or noisy, although the speaker is active. The incorrectly determined inactive rate is somewhat high for Speakers 2 and 3. These resultsreflect the fact that the speech volume levels of Speakers 2 and 3 are lower than Speaker 1.

7. Conclusion

This paper proposes a novel scheme for tracking intermittently speaking multiple speakers. In the proposed tracking method, the number of active speakers can be estimated using the observed covariance matrix and the estimated noise-only-reverberant covariance matrix (see Section 3). Then the active speakers are identified using the decomposed likelihood function. Finally all speakers including inactive ones can be tracked using a particle filtering. The proposed method was evaluated using live recordings in the case of three-speakers and the results show that the proposed method produces highly accurate tracking results.

Currently we are concerned with our tracking method being applied in such fields as interfaces between humans and robots or data processing for meetings, and hence we dealt with the case of tracking speech/speakers. However, the proposed method can be applied to the tracking of other types of source, such as musical instruments or vehicles, because we do not use any special properties of speech for tracking. In this paper we tested our approach with a three speaker case. How many targets can be tracked with this approach is also an interesting future research issue.

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