

# Accurate Tracking of Mobile Terminals by Modified Particle Filtering

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## 1. Introduction

Toward 4th generation mobile communication, it is very important to know the electromagnetic wave propagation environment accurately in advance; from which direction the incident signals are coming from. We must pay attention to the situation that the Direction Of Arrival (DOA) changes every single time (snapshot) when using mobile phones in moving objects like trains or cars. When DOA changes every single time, we can use only a small number of snapshots because we cannot use old data that are collected at different locations. It leads bad estimate accurately, as it is well-known that the estimation accuracy becomes worse when we employ MUSIC method [1] with small number of snapshots. LMS, RLS algorithms are capable of estimating DOA of moving terminals using reference information, but their estimation accuracy becomes worse when DOAs of two (or more) terminals are coming close to each other. Therefore, we need an algorithm which can accurately estimate DOAs of moving terminals with less number of snapshots.

Here we focus on the algorithm of particle filter which is able to estimate a state of moving objects when you cannot know it directly [2]–[4]. An approach by Asano et al [4] can extract a human voice from accurate particle distribution when we have the source number in advance. Actually the particle filter requires large computational cost that is negligible in processing acoustic signals but cannot be negligible for communication signals.

In this paper, we first modify the algorithm of particle filter to reduce its computational cost, and then apply it to estimate DOAs and to track mobile communication terminals. We discuss the estimation accuracy in comparison with the other algorithms.

## 2. Preliminaries: Particle Filter

Processing of Particle Filter is briefly summarized as (a) determine the location of particles at the time  $t$ , (b) calculate the likelihood for each particle, (c) increase or selection of particles, and (d) state transition (to the time  $t + 1$ ). The input signal vector  $\mathbf{y}$  is written as

$$\mathbf{y}(t) = \sum_{\ell=1}^L \mathbf{a}_{\ell}(t)s_{\ell}(t) + \mathbf{n}(t) \quad (1)$$

where  $L$ ,  $s_{\ell}$ ,  $\mathbf{a}_{\ell}$ ,  $\mathbf{n}$  are the number of incident signals,  $\ell$ -th incident signal, the array mode vector corresponding to  $s_{\ell}$  and the noise vector, respectively. The likelihood function for the input signal  $\mathbf{y}$  is equivalent to the weight in (b), i.e.,

$$P(\mathbf{y}_t|\mathbf{x}_t) = \exp(\text{tr}[\mathbf{C}_y \mathbf{K}_y^{-1}]) \quad (2)$$

where  $\mathbf{C}_y$  and  $\mathbf{K}_y$  denote the sample covariance and the model covariance, respectively [1],[2]. By increasing or selecting particles, the distribution of particles become a well approximation of the probability distribution.

In the state transition process, we use the state transition probability and the current state vector  $\mathbf{x}_t^{(i)}$  to predict the next state vector  $\tilde{\mathbf{x}}_{t+1}^{(i)}$ . Then we calculate the posterior probability distribution  $\mathbf{p}(\mathbf{x}_t|\mathbf{y}_{1:t})$  that can be approximated by

$$\mathbf{p}(dx_t|\mathbf{y}_{1:t}) \simeq \sum_{i=1}^N \tilde{\omega}_t^{(i)} \delta_{\mathbf{x}_t^{(i)}}(dx_t) \quad (3)$$

where  $\tilde{\omega}_t^{(i)}$  denotes the weight for each particle, and  $\delta_{\mathbf{x}_t^{(i)}}(dx_t)$  denotes the Dirac's delta function that becomes one when the state  $\mathbf{x}_t^{(i)}$  becomes within the infinitesimal distance  $dx_t$ . The transition probability  $\mathbf{p}(\mathbf{x}_t|\mathbf{x}_{t-1})$  and the posterior probability  $\mathbf{p}(\mathbf{x}_{t-1}|\mathbf{Y}_{1:t-1})$  are referred in the location of particles since the particles are distributed based on those probability distributions.

### 3. Modified Particle Filtering based on 1-D DOA estimation

As the source number  $L$  becomes larger, the dimension of the parameters to be searched gets larger. It means that the peak search of probability distribution becomes multidimensional (m-D) optimization problem and will require large computational cost. Therefore we propose two different approaches based on one-dimensional (1-D) estimation and does not require m-D estimation to reduce the computational cost.

#### 3.1 Tracking by Multiple 1-D estimation

When we estimate DOA of only one wave even though true number of waves is two, Particle filter can estimate the DOA of one of two waves with larger power. After specifying the DOA of the first wave (with larger power), we can estimate the DOA of the second wave (with smaller power) while fixing the DOA of the first wave. Then we can estimate two DOAs by twice processing of 1-D DOA estimation (Space does not permit the detailed explanation).

#### 3.2 Tracking by Notch filter-based Estimation

Here we present a method to detect 2 waves by using Notch filter. First we let  $\ell$  of  $\mathbf{a}_\ell$  in eq.(1) be 1, even though there are two or more incident waves, and estimates the DOA of the first wave by Particle Filter of 1-D estimation. Then we make  $(M - 1)$  pairs of received signals by neighboring elements like (1,2), (2,3), ...,  $(M - 1, M)$  for total  $M$  array elements. Making the pairs has been done by multiplying the Notch array mode vector

$$\mathbf{a}_\ell(t) = \left[1, -e^{+j\pi \sin \phi}\right] \quad (4)$$

to the input signal vector, now we can eliminate the signal from the direction of  $\phi$ . We also can increase the number of the elements to be used for Notch filtering, we can design accurate Notch filter beam pattern. In the case of  $n$  elements are used for Notch filter, the array mode vector of notch filtering can be written as

$$\mathbf{a}_\ell(t) = \left[1, -\frac{1}{n}e^{j\pi \sin \phi}, \dots, -\frac{1}{n}e^{jn\pi \sin \phi}\right] \quad (5)$$

Multiply the mode vector of eq.(5) to the input signal vector, we have the modified signal vector of  $(M - n + 1)$  elements that the signal from the direction  $\phi$  is well-eliminated. Fig. 2 shows the Notch beam patterns when we change the number of array elements to be used as Notch filtering as 2,3 and 4 elements while fixing the total array elements as 8 and the eliminated DOA as  $-30^\circ$ , respectively. From this result, we can see that more sharp Notch beam is certainly designed as the number of Notch elements becomes larger.

## 4. Simulation

### 4.1 Specifications of simulation

Table 1 shows the specifications of the following simulations.

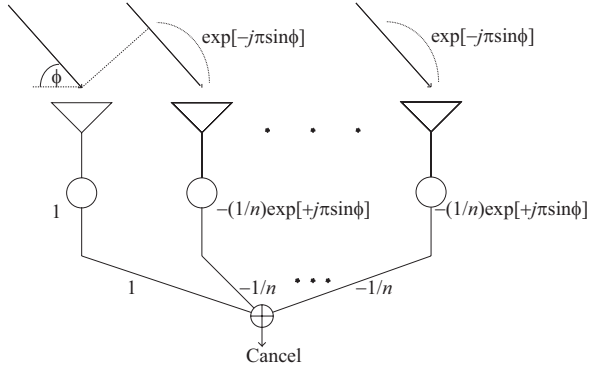


Figure 1: Configuration of Notch system for signal elimination.

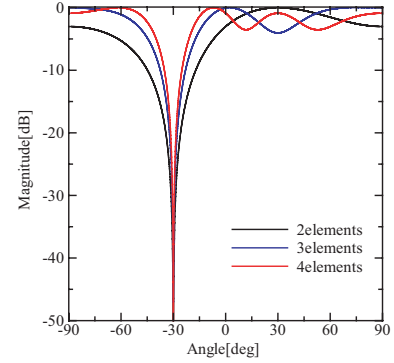


Figure 2: Beam pattern of Notch filter.

Table 1: Specifications of simulation

# of elements	8
Array interval	half-wavelength
Modulation type	QPSK
SNR	10[dB]
SIR	1.76[dB]
Step size (LMS)	0.01
Forgetting factor (RLS)	0.95

## 4.2 Comparison with proposed methods

First we compare the multiple 1-D estimation (method 1) and the Notch-based estimation (method 2). Note that we employed 4 elements for notch filtering. Fig. 3 shows the tracking results of two moving objects. From Fig. 3, we found that the method 1 becomes more accurate when the DOAs of moving objects are getting closer. For all the other cases, the method 2 becomes more accurate and also realizes less computational cost than the method 1. Therefore, we hereafter employ the method 2 as the proposed method.

## 4.3 Snapshot dependency

Next, we evaluate the snapshot dependency of the proposed algorithm in comparison with MUSIC method. The result is shown in Fig. 4. We could confirm that the estimation accuracy of Particle Filter was good for the case of the small number of snapshots like less than 10.

## 4.4 Tracking of Moving Terminals

We compare the proposed method with LMS and RLS algorithms from the viewpoint of tracking performance. For LMS and RLS algorithms, we first form the beam and then find the peak of the beam which is equivalent to the estimated angles.

Fig. 5 and Fig. 6 show the tracking results of 1st (desired, black line) and 2nd (interference, green line) waves, respectively. We see that LMS and RLS cannot estimate the DOA in the vicinity of 1.5[sec] because the DOAs of two waves are getting very close. However, we can confirm much more accurate tracking performance of the proposed algorithm based on Particle Filtering. Especially the tracking of the 1st wave is almost perfect when the DOAs are very close and LMS & RLS can hardly track the 1st wave. This is due to the property of the particle filter that can extract only the maximum power signal. We also found that the RMSE of the proposed method is around  $2^\circ$  smaller than LMS and  $4^\circ$  smaller than RLS on the average.

## 5. Concluding remarks

In this paper, we proposed a accurate tracking algorithm of mobile terminals based on In the situation where LMS and RLS cannot accurately estimate, Particle Filter was able to estimate

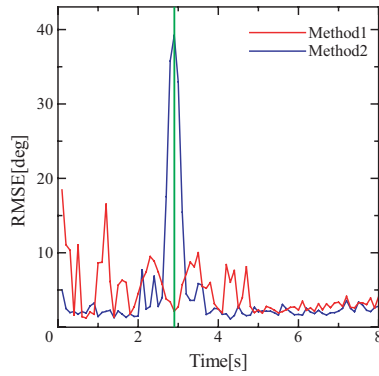


Figure 3: Comparison with proposed methods

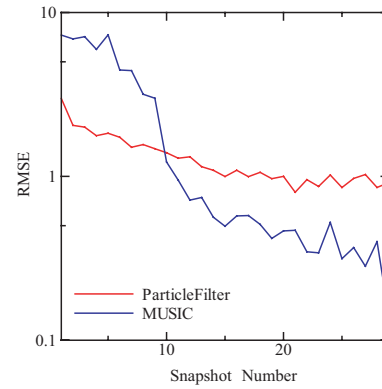


Figure 4: Snapshot dependency

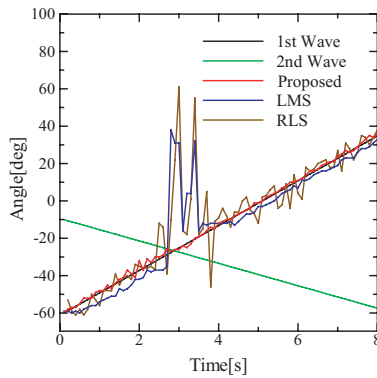


Figure 5: Tracking result of the desired wave

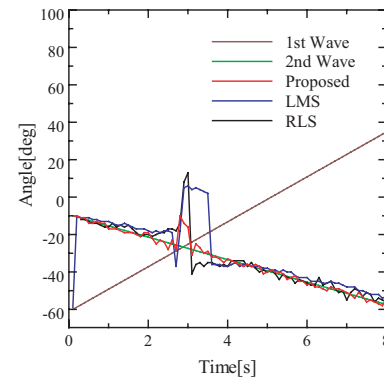


Figure 6: Tracking result of the interference wave

the DOAs of moving terminals accurately. Actually, for MUSIC method, what cannot chase the situation of a current arrival direction by using storing old data, old data is nominated for a problem. With a small number of snapshots, means only with the latest data, Particle Filter can be said to be superior in a point that an estimate is possible. However, the likelihood that needs a calculation whenever a new signal enters is big load, that still remains as one of future studies.

## References

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