A Probability-Based Acoustic Source Localization Scheme Using Dual-Microphone Smartphones

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***Abstract*—This paper proposes a new acoustic source localization scheme, called Probabilistic Cutting Method (*PCM*), with randomly deployed smartphones which equipped with known location and direction dual-microphones. Instead of using the value of TDOA (Time Difference Of Arrival), we just use binary information (0/1) and probability to convert the localization problem into plane cutting issues. We can easily come up with the Basic Cutting Method (*BCM*), but it may appear empty set when error (location error, angle error or error anchors) occurs. *PCM* can effectively avoid the problem along with lower positioning error. When comparing *PCM* with TDOA and *BCM* in different aspects, simulation evaluation results indicate that *PCM* algorithm achieves highly robustness and accuracy.**

***Index Terms*—Acoustic Source Localization, Binary Information, Probability**

I. Introduction

The growing scale and importance of computer technology has driven the wide utilization of acoustic source localization techniques in many occasions including locating speakers in a room [1], shooter localization [2], network routing, surveillance [3], target tracking [4], and emergency response. Most existing localization technologies based on microphone arrays usually have problems of low computing capacity, high system costs, and low positioning accuracy in the presence of reverberation environment.

The traditional microphone array-based localization systems have been thoroughly studied in the literature. Despite their obvious advantages over single-microphone systems, traditional microphone array-based localization systems have their limitations because they usually sample the sound fields only locally, typically at a relatively large distance from the sound source(s). Furthermore, due to the constraints of space and energy, especially in miniature and portable devices, the array is often limited in physical size and processing power, what's more, it demands strict GCC (Generalized Cross-Correlation) algorithm [5], [6].

Given these limitations, we believe there is an opportunity to propose a time-synchronized method, in this paper, we explore to locate a single acoustic source, and it makes three major contributions, which can be described as follows:

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(1) Synchronization free. We adopt smartphones which have dual time-synchronized microphones to remove the time-synchronized requirements of conventional localization methods.
(2) Low costs, easy deployment. We implement a simple GCC algorithm to weaken the demand of hardware to compute the value of TDOA with randomly deployed smartphones, by leveraging binary information and probability to locate the target.
(3) High robustness and accuracy. Simulation results indicate our algorithm has strong robustness and high accuracy when location error, angle error and error anchors exist.

The rest of this paper is organized as follows: Related work is reviewed in Section II. Section III presents the system overview. Section IV states a simple method, but it may involve empty set. In Section V, we introduce the detailed design of PCM algorithm. The simulation of the system is evaluated in Section VI. Finally, Section VII summarizes the conclusions and future works.

II. Related Work

Based on whether to calculate the distance between n-odes, the current localization methods can be classified into two kinds: range-based and range-free [7]–[9]. Range-based method includes RSSI (Received signal strength indicator) [10]–[12], TOA (Time of arrival) [13], [14], TDOA (Time difference of arrival) [15], [16]. Range-free method can be implemented by geometric methods, e.g., MDS (Multi dimensional scaling) [17], DV-Hop (Distance vector-hop) [18].

Acoustic source localization is a well-studied problem. The existing methods can be divided into four major categories: RSS (Energy-based/received signal strength) [19], [20], AOA (Angle of arrival) [21], TOA [22], and TDOA [16]. The RSS method does not require time synchronization, however, it is very sensitive to channel conditions. AOA method need to be equipped with at least two microphones on each node, as well as complicated microphone array processing techniques, and demands high computational complexity. The TOA algorithm employs the information of accurate signal transmission time from source to the receiver; what's more, it must pay attention to time synchronization among participating nodes. Compared

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to TOA, the TDOA model considers the difference of the arrival times between the two clock-synchronized microphones, without knowing the starting time of the acoustic source.

A high accuracy acoustic ranging system using COTS (commercial-off-the-shelf) mobile devices, like cell phones and PDAs, is designed and implemented [15]. Liu *et al.* [23] propose an indoor localization ecosystem Guoguo consisting of an anchor network via smartphones. Without cooperation of the object and much knowledge about the environment, Fu *et al.* [24] present a novel value-based estimation algorithm named *Orthogonal Cut (OC)* for event localization. Both our work and *OC* algorithm can locate the acoustic source using plane cutting, but they are different mainly in three aspects: (i) Our algorithm is sufficient to locate the target even the smartphones are deployed randomly, for *OC*, however, it is suitable for special network topology, and almost impossible with randomly placed sensors. (ii) We use dual-microphone smartphones to reach non-synchronization, yet *OC* demands for synchronized sampling intervals for the value-based estimation. (iii) The computing complexity of our algorithm is *O(n)*, while that of *OC* is generally between n^2 and n^3, if the number of sensors is n.

III. SYSTEM OVERVIEW

In this section, we focus mainly on the system overview of our scheme, which aims at locating an unknown acoustic source. Let us consider that an 2D localization space consisting of distribution of N known sensors (anchors), each accommodating 2 microphones, and the distance between the two microphones are fixed. Fig. 1 shows the layout of our problem, which means we deploy lots of smartphones in large scale. The N anchors can be defined as S, and $S = \{s_1, \cdots, s_i, \cdots, s_N\}$, where $s_i = \{node_{2i-1}, node_{2i}\}$, along with any node $node_i$ has its location coordinates denoted as $[x_i, y_i]$, with the direction of α_i. In the presence of reverberations, for ith smartphone, if we draw a perpendicular bisector to the line joining of its two microphones, it can divide the localization space into two regions, we can use a matrix $Binary\_data$ to store the corresponding binary information about the target to the anchors, and it can be defined as

$$Binary\_data(i) = \begin{cases} 1 & \text{if} \quad TDOA(i) \geq 0, \\ 0 & \text{if} \quad TDOA(i) < 0, \end{cases} \tag{1}$$

where $1 \leq i \leq N$, $TDOA(i)$ is the value of TDOA for the target to the ith anchor.

However, when the location and direction of microphones are known, just using the information about microphones to locate the target is very difficult. A simple method named Basic Cutting Method can be easily thought out, but it may not locate in some cases, we will introduce it in next section.

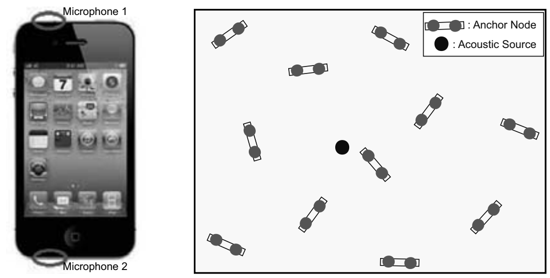


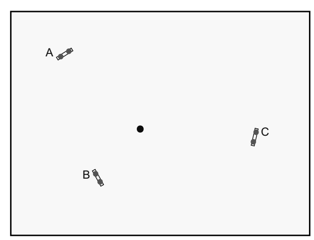
Fig. 1. System overview. A sensor network formed by randomly deployed smartphones equipped with known location and direction microphones to locate the acoustic source. Input: $([x_i, y_i], \alpha_i, Binary\_data(i) \in \{0, 1\})$ Output: The target's location L_t.

IV. BASIC CUTTING METHOD

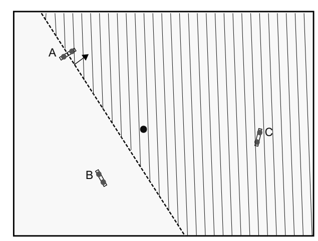
In fairly reverberant conditions, we can use the binary information of the target to cut the plane, discard the blocks that do not conform the requirements, then we can determine the general direction of the target. For ith node, we can define $R(i)$ as the approximate range of the target according the binary information about the anchor,

$$R(i) = \{x_i | Binary\_data(x_i), x_i \in R\} \tag{2}$$

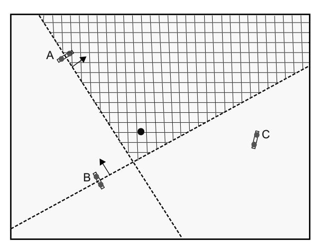
where R represents the area of test room.



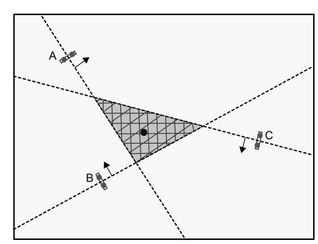
(a) Three anchors and one target.



(b) $R(A)$: The range which includes the target by using A to cut the plane.



(c) $R(A) \cap R(B)$: Using A and B to cut the plane, reserving the overlap.

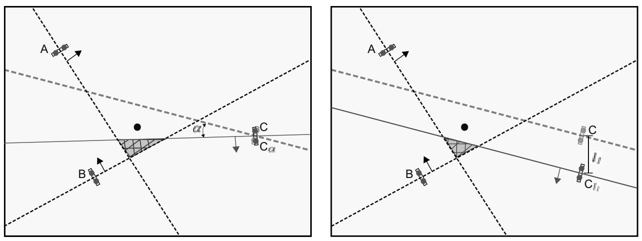


(d) $R(A) \cap R(B) \cap R(C)$. Using A, B and C to cut the plane, reserving the overlap.

Fig. 2. Example of using Basic Cutting Method to locate the target with three anchors. The direction of arrows filling with different lines are the general range. The overlap of 2(d) is the final range.

As shown in Fig. 2, we have three anchors A, B and C in the test room, once using the binary information of A to cut the plane, we reserve the plane when binary information equals to 1, and filling the direction of arrow with lines in Fig. 2(b), so we can get the range named $R(A)$ including the target. After repeating the process shown in Fig. 2(c) and Fig. 2(d), we can get $R(A) \cap R(B) \cap R(C)$ represented by the overlap as the final cell of target, by taking the geometric center of the overlap to locate the target. From Fig. 2(a) to Fig. 2(d) can thoroughly describe the process of the Basic Cutting Method (*BCM*).

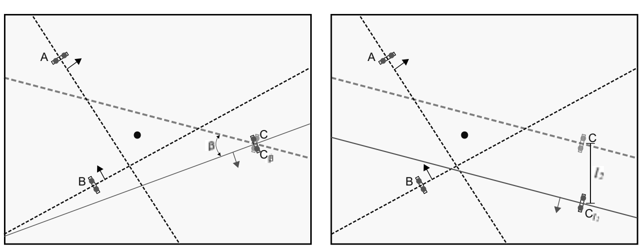
Although *BCM* may get the location of the target with the binary information for the target to the given anchors. When error anchors come, which means the anchors mistake the right side for the wrong one, it is easily prone to lose available information when failed to judge. But for location error or angle error of anchors, it differs in different cases. Fig. 3 shows a little angle error and location error of anchors that we can also locate the target.



(a) Angle error α of anchor (b) Location error l_1 of anchor

Fig. 3. Case for a little location error and angle error that won't lead to the empty set with Basic Cutting Method.

Fig. 4 displays some cases leading to empty set, say, when we fail to locate, we can't get a range which includes the target. As shown in Fig. 4(a), when there exist no error, we can easily know the target is below the perpendicular bisector of C. But if C has angle error shown as C_β, and when we use it to cut the plane, we still think the target is below the perpendicular bisector of C_β, this can lead to $R(A) \cap R(B) \cap R(C_\beta) = \emptyset$, so we will fail to locate. In Fig. 4(b), once C occurs location error to become C_{l_2}, just like Fig. 4(a), we also suppose the target is below the perpendicular bisector of C_{l_2}, after calling Incise(), we will get $R(A) \cap R(B) \cap R(C_{l_2}) = \emptyset$ which dues to empty set.



(a) Angle error β of anchor (b) Location error l_2 of anchor

Fig. 4. Case for errors lead to empty set ($R(A) \cap R(B) \cap R(C) = \emptyset$) for the Basic Cutting Method.

V. Probabilistic Cutting Method

After a reasonable amount of experiments and discussion, we have exploit a method that leverages probability to solve the problem of empty set related to *BCM*, which is called Probabilistic Cutting Method (*PCM*). We also cut the plane and reserve all the region with a special set of probabilities $P = \{p_1, \cdots, p_i, \cdots, p_N\}$ to judge the most likely information of the two microphone nodes. As shown in Fig. 5, according to (3), the probability of the target to the right side of the anchor C is p, then the left is $1 - p$. When all the anchors are defined with probability, then we can use the weighted probabilities to locate the target. According the definition of probability, $p \in [0, 1]$. For the probabilistic theory in our algorithm, if $p \leq 0.5$, we can't obtain more relatively accuracy. So $p > 0.5$ should be guaranteed to *PCM*.

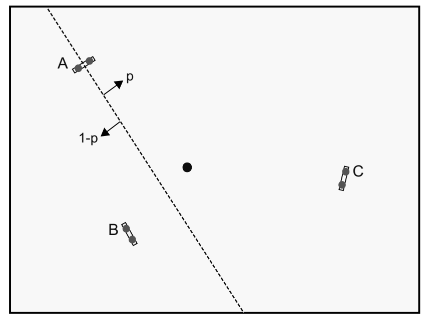


Fig. 5. Example of Probabilistic Cutting Method using probability p to cut the plane.

$$p_i = \begin{cases} p & \text{if} \quad R(i) \neq \emptyset, \\ 1 - p & \text{if} \quad R(i) = \emptyset, \end{cases} \tag{3}$$

where p is the probability that we choose for *PCM*.

In real situation, we can't avoid reverberation and noise, so we can't get very accurate acoustic signal. For SNR (signal-to-noise ratio) can stand for the quality of the acoustic signal, we can assume that SNR is consistent with p. The formula (4) shows the definition of SNR where S/N is the energy ratio of acoustic signal and the noise. If we compute the energy of the sound when there exist no sound, we will get $SNR = 0dB$. If there exist some sound, then the energy of the sound will enlarge, the value of SNR will increase. Using mathematical analysis, we get the formula (5)

$$SNR = 10 * lg(S/N) \tag{4}$$

$$p(SNR) = 0.5 + \frac{\arctan(0.1 * SNR)}{\pi}, \tag{5}$$

where $p(SNR)$ is a function about probability and SNR. Fig. 6 shows the relationship between probability p and SNR, from Fig.6, we can know, when SNR increases, p becomes bigger and bigger, infinitely close to 1.

In probabilistic theory and statistics, the expected value of a discrete random variable is the result of a random test which is repeated several times under the same opportunities to calculate the average equivalent value called expectation. With no loss of generality, we can use expectation $E(p)$ to determine the appropriate probability p for *PCM*. And we can

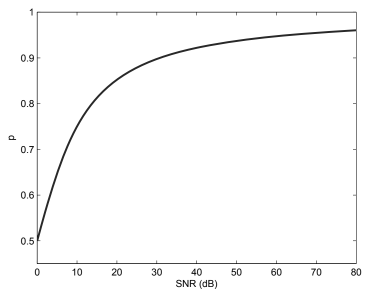


Fig. 6. The probability p for PCM versus SNR.

get

$$E(p) = \frac{\int_{SNR_{min}}^{SNR_{max}} p(SNR) \cdot d(SNR)}{SNR_{max} - SNR_{min}}, \quad (6)$$

where SNR_{min} is the lower bound and SNR_{max} the upper bound of SNR. In pursuit of the most suitable value, we evaluate a reasonable amount of experiments and find it will achieve the best positioning accuracy performance when the value of SNR is between $10dB$ and $20dB$, from the formula 6 we will get $E(p) = 0.81$, so we use $p = 0.81$ for all anchors to cut the plane in this paper.

Algorithm 1: The *PCM* Algorithm

Input: Probability to cut the plane: p
The discrete grid point set of the room: R
0/1 information set about the target: $Binary\_data$
Output: Estimated location: L_t

1 Initialize the cumulative probability set $P\_total \leftarrow 0$;
2 **for** *Each anchor* $j \in N$ **do**
3 **if** *the target is on the exact side of* j*:* $Binary\_data(j) == 1$ **then**
4 $R(j) \leftarrow p$;
5 **end**
6 **else**
7 $R(j) \leftarrow 1 - p$;
8 **end**
9 Cumulate the probability stored in P_total;
10 **end**
11 L_t=Taking_target(P_total, R);
12 **return** the estimated position: L_t;

Algorithm 1 defines a cutting function from Step 1 to 10, whose function is to narrow the range of the target with the given condition. If the target is in the exact side of the target, we reserve the range with the probability p, then the probability of the target in the opposite side is $1-p$. By using recursive algorithm, after using all anchors to cut the plane, we can finally get an approximate range of the target which is represented by R, then we can call a function to compute the coordinates of the target shown in line 11.

In line 11, we define a weighted probability set $Weight$, whose definition is showed in equation (7) and it cumulates the probability of all points in the room. By using recursion, we can get the position of the target when it satisfies the equation (8). The Fig. 7 shows the relationship between the weighted probability and the discrete point set in the room, the red region is the final range of the target, we finally take the peak of the probability containing the range of the target.

$$Weight(i) = \sum_{i=1}^{N} p_i. \quad (7)$$

$$L_t = arg \max_{i \in N} Weight(i). \quad (8)$$

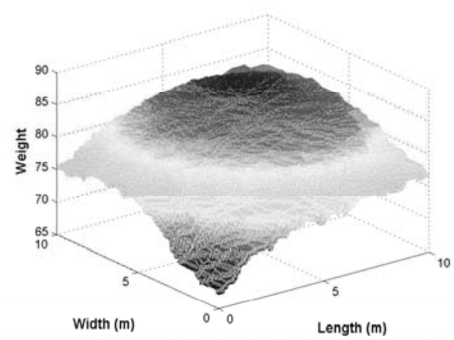


Fig. 7. The figure of weighted probability in discrete grid point usingPCM, the deep red color is the target range we get when we take the peak of probability.

The complexity analysis of the proposed method depends mainly on computation, for *PCM* uses the binary information to cut the plane, if we deploy n anchors in the field, the plane will be cut by n times, so the computational complexity is $O(n)$.

VI. Simulation Evaluation

In this section, we try to simulate our acoustic source localization algorithm with TDOA method and *BCM* using MATLAB in a reverberant room. In the simulation, we randomly generate a lot of smartphones in a 10×10 m area. And it is organized in an acquisitions that the position and angle of all anchors are assumed to be known in advance. To reduce the impact of the uncertainty of position and orientation to smartphones on the accuracy of localization, we add a certain amount of angle error and location error in all the simulations. As mentioned in Section V, we choose 0.81 for the probability to cut the plane . All the statistics are running 1000 times for high confidence, and reported by CDF figure. Table 1 illustrates the default simulation setup parameters.

A. Comparison with TDOA

We try to compare *PCM* and *BCM* with common acoustic localization method TDOA. TDOA can use any group of

TABLE I
DEFAULT CONFIGURATION PARAMETER

Parameter	Description
Field Area	10m ×10m
Number of Anchors	40
Location Error Range	0.10m
Angle Error Range	5 degrees
Random-Seed Loop	1000 times

three microphones to estimate the target's position. In the simulation, all parameters remain default, we sort the RMSE (root mean square error) results of TDOA by ascend and choose the 20th percentile measurements in comparison with *PCM* shown in Fig. 8. As expected, *PCM* and *BCM* perform better than TDOA, which dues to the fact that errors can be additive for all anchors used for TDOA.

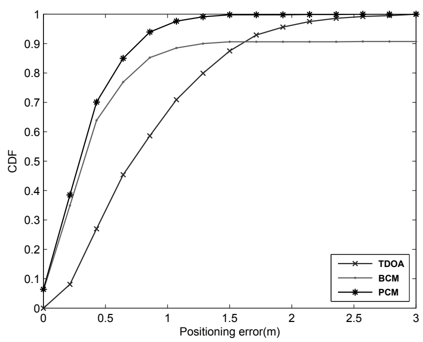
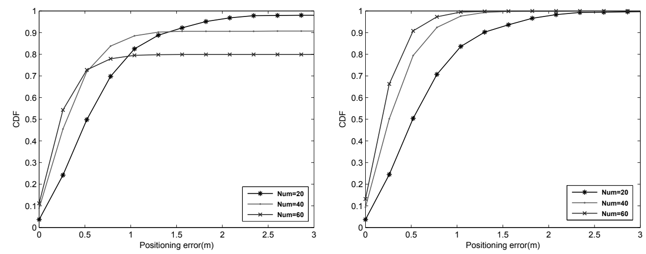


Fig. 8. Comparison with *BCM* and TDOA.

B. BCM *vs* PCM

1) Impact of the number of anchors: In this experiment, we investigate the localization error and number of anchors with different number of anchors. Since the two methods aim to narrow the range of the target by processing all anchors, we can except that with more anchors, the whole area will be divided into more small parts, so more accurate localization estimation could be achieved by *PCM*. As shown in Fig. 9(a) and Fig. 9(b), we choose 20, 40, 60 anchors to express the CDF and positioning error for the two methods. With the number of anchors increases, for *BCM*, not all cases can locate the target for the curve can't reach 100%, with the basis on *BCM* is to discard the plane which does not meet the requirement, so when the number of anchors increases, more parts will be abandoned, so the chance for empty set grows. Fig. 9(b) demonstrates that the localization error rate decreases as the number of anchors increases for *PCM* and we can always get the positioning result as the curve can reach 100%, because it reserves regoins that does not meet the requirements with a certain probability instead of discarding them simply, in order to avoid the empty set.

2) Impact of the number of error anchors: For *BCM* discards the plane, we can assume that it is sensitive to the



(a) Basic Cutting Method (b) Probabilistic Cutting Method

Fig. 9. Impact of the number of anchors for the two methods.

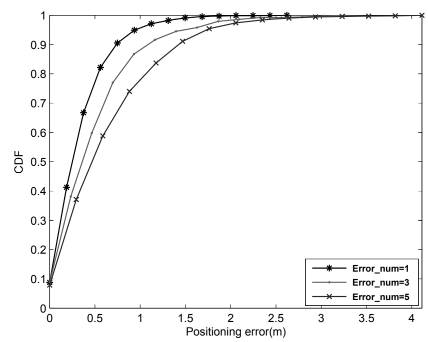
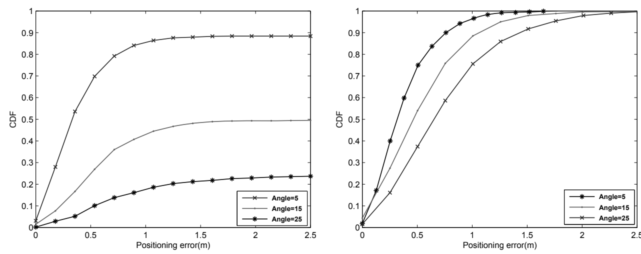


Fig. 10. Impact of the number of error anchors.

anchor error. In this experiment, we try to simulate *PCM* by using different number of error anchors, which give the wrong binary information. Since the number of error anchors can affect the localization accuracy, we image that the more error anchors exist, the bigger the localization error is. And Fig. 10 confirms our imagination, it indicates that as the number of error anchors increases, the positioning error of *PCM* is much smaller than that of *BCM*. It shows although error anchors appear, *PCM* can awalys get positioning result, so it achieves fault tolerance.

3) Impact of the angle error: In the experiment, we perform the impact of the angle error of anchors for *BCM* and *PCM*. As the direction of anchors are uncertain, we assume the angle error may influence the localization accuracy. The Fig. 11 confirms it. As shown in Fig. 11, the positioning errors for the two methods are rising as angle errors of anchors increase. So we have sufficient confidence to conclude that angle error of anchors will influence the localization accuracy. In particular, in Fig. 11(a), when angle errors exist, no more than 90% anchors can locate the target for *BCM* and about 90% anchors can reach $1m$ positioning error when the angle error is 5 degrees. If the angle error is 25 degrees, nearly 20% anchors can get $1.5m$ positioning error. In Fig. 11(b), when angle errors increase, the positioning error for *PCM* is much more smaller than that of *BCM* as shown in Fig. 11(a), so the localization accuracy of *PCM* is much higher than that of *BCM* in the presence of angle error.

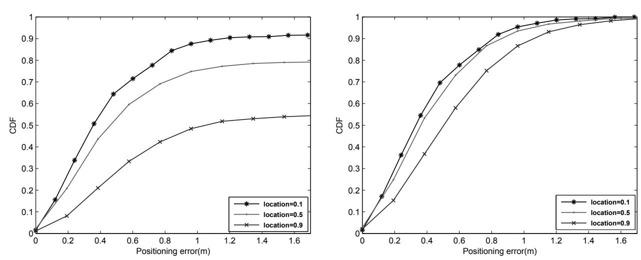
4) Impact of the location error: In this experiment, we try



(a) Basic Cutting Method (b) Probabilistic Cutting Method

Fig. 11. Impact of the angle error.

to compare *BCM* with *PCM* using location error of anchors. In Fig. 12, we choose the location error with $0.1m$, $0.5m$ and $0.9m$ to test the positioning performance for the two methods. Fig. 12 indicates the location error of anchors has an effect on the positioning results. With greater location errors, the localization accuracy of *PCM* is higher than *BCM*. For *BCM*, the positioning error changes obviously as location error increases in Fig. 12(a). However, as demonstrated in Fig. 12(b), the positioning error varies little, which demonstrates *PCM* is more robust than *BCM*.



(a) Basic Cutting Method (b) Probabilistic Cutting Method

Fig. 12. Impact of the location error.

VII. Conclusions and Future work

This paper presents *PCM*, a novel acoustic source localization scheme that uses dual-microphone smartphones. We can convert the localization problem into plane cutting issues by using probability and binary information to locate the target. A simple method named *BCM* can locate the target, but it can arise empty set problem, however, *PCM* can effectively solve it. Simulation evaluation results demonstrate that the *PCM* is much more accurate than TDOA and *BCM*, besides, *PCM* achieves fault tolerance, good accuracy and great flexibility with low cost when errors exist.

As ongoing and future work, we hope to solve the indoor localization problem without knowing anchors' location information in advance, what's more, we also try to locate multiple targets.

Acknowledgments

This work is supported by Natural Science Foundation of China (Grants No. 61070181, No. 61272524 and No.61202442) and the Fundamental Research Funds for the Central Universities (Grants No.DUT14ZD218 and No. DUT14QY29). This work is also supported by Specialized Research Fund for the Doctoral Program of Higher Education (Grant No. 20120041120049).

References

[1] Y. Guo and M. Hazas, "Localising speech, footsteps and other sounds using resource-constrained devices," in *IEEE/ACM IPSN*, 2011.
[2] J. Sallai, Á. Lédeczi, and P. Völgyesi, "Acoustic shooter localization with a minimal number of single-channel wireless sensor nodes," in *ACM SenSys*, 2011.
[3] Y. Guo and M. Hazas, "Acoustic source localization of everyday sounds using wireless sensor networks," in *ACM UbiCom*, 2010.
[4] W.-P. Chen, J. C. Hou, and L. Sha, "Dynamic clustering for acoustic target tracking in wireless sensor networks," *ACM MOBICOM*, 2004.
[5] A. Canclini, E. Antonacci, A. Sarti, and S. Tubaro, "Acoustic source localization with distributed asynchronous microphone networks," *IEEE Transactions on Audio, Speech, and Language Processing*, 2013.
[6] E. Masazade, R. Niu, P. K. Varshney, and M. Keskinoz, "Energy aware iterative source localization for wireless sensor networks," *IEEE Transactions on Signal Processing*, 2010.
[7] K. Yedavalli and B. Krishnamachari, "Sequence-based localization in wireless sensor networks," *ACM MOBICOM*, 2008.
[8] Z. Zhong, T. Zhu, D. Wang, and T. He, "Tracking with unreliable node sequences," in *IEEE INFOCOM*, 2009.
[9] Q. Wang, R. Zheng, A. Tirumala, and a. o. Liu, "Lightning: a hard real-time, fast, and lightweight low-end wireless sensor election protocol for acoustic event localization," *ACM MOBICOM*, 2008.
[10] V. S. Au A W S, Feng C *et al.*, "Indoor tracking and navigation using received signal strength and compressive sensing on a mobile device," in *IEEE Transactions on Mobile Computing*, 2013.
[11] Y. Kim, H. Shin *et al.*, "Smartphone-based wi-fi pedestrian-tracking system tolerating the rss variance problem," in *IEEE PerCom*, 2012.
[12] S. Yang, P. Dessai *et al.*, "Freeloc: Calibration-free crowdsourced indoor localization," in *IEEE INFOCOM*, 2013.
[13] Q. Wang, W.-P. Chen, R. Zheng, K. Lee, and L. Sha, "Acoustic target tracking using tiny wireless sensor devices," in *IEEE/ACM IPSN*, 2003.
[14] S. Venkateswaran and U. Madhow, "Localizing multiple events using times of arrival: A parallelized, hierarchical approach to the association problem," *IEEE Transactions on Signal Processing*, 2012.
[15] J. Qiu, D. Chu, X. Meng, and T. Moscibroda, "On the feasibility of real-time phone-to-phone 3d localization," in *ACM SenSys*, 2011.
[16] B. Xu, R. Yu, and a. o. Sun, "Whistle: Synchronization-free tdoa for localization," in *IEEE ICDCS*, 2011.
[17] M. Jin, S. Xia, Wu *et al.*, "Scalable and fully distributed localization with mere connectivity," in *IEEE INFOCOM*, 2011.
[18] D. Niculescu and B. Nath, "Dv based positioning in ad hoc networks," *Telecommunication Systems*, 2003.
[19] A. M. Hossain and W.-S. Soh, "Cramer-rao bound analysis of localization using signal strength difference as location fingerprint," in *IEEE INFOCOM*, 2010.
[20] W. Cheng, K. Tan, V. Omwando, Zhu *et al.*, "Rss-ratio for enhancing performance of rss-based applications," in *IEEE INFOCOM*, 2013.
[21] L. M. Kaplan, Q. Le, and N. Molnar, "Maximum likelihood methods for bearings-only target localization," in *IEEE ICASSP*, 2001.
[22] K. Liu, X. Liu, L. Xie, and X. Li, "Towards accurate acoustic localization on a smartphone," in *IEEE INFOCOM*, 2013.
[23] K. Liu, X. Liu, and X. Li, "Guoguo: enabling fine-grained indoor localization via smartphone," in *IEEE MobiSys*, 2013.
[24] D. Fu, M. Becker, S. Schaust, and H. Szczerbicka, "Orthogonal cut algorithm for value-based event localization in sensor networks," in *IEEE MASS*, 2012.