Implementation of a real-time sound source localization method for outdoor animal detection using wireless sensor networks

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***Abstract*—We propose an identification method of sound source locations in outdoor areas by employing direction-of-arrival (DOA) measurements obtained from a microphone array. In determining the locations of sound sources, at least two microphones must record the same sound. Existing methods implicitly assume that sound sources are distributed in an area surrounded by the microphone arrays. They also imply that the "sound-observable" range of the microphones should exceed the maximum distance between microphones. In an outdoor field, however, microphone-array-deployable areas are limited as just in our field case. That is, those conditions are not always met, and accurate microphone positions cannot be obtained. By locating microphone arrays close to each other, the overlapping area observed by them is enlarged and also their positions can be accurately measured. However, since most existing localization methods do not consider sound sources outside the area surrounded by the microphone arrays, they cannot achieve both of real-time and accurate localization. We propose a method with less computational complexity while obtaining high level of accuracy. Simulation results show that the proposed method can reduce the computation time by 90% while obtaining the same estimation accuracy as the existing method. Moreover, our proposed method achieves a good estimation accuracy with an average error of less than 60 cm in outdoor experiments.**

Index Terms*—*direction of arrival (DOA), microphone array, wireless sensor network, real-time computation, animal detection

I. Introduction

Mathematical models inspired by biological mechanisms help us to develop robust and adaptive systems in the field of information communications technology [1]. As part of this interdisciplinary research progress, mathematical modeling research into biological systems has been facilitated by the development of experimental techniques and enhanced computer performance. Specifically, various studies have applied *swarm intelligence*; i.e., cooperative social behavior that emerges from the autonomous motion of individuals, to network control [2]. For that purpose, we are now focusing on the calling behavior of Japanese tree frogs (Fig. 1), in which only the males produce successive calls to attract female frogs and advertise their territory to other males. Previous indoor experiments have demonstrated that two male frogs can alternate their calls [3], behavior which is known as anti-phase synchronization. Recently, we discovered another aspect

Fig. 1. Photograph of a Japanese tree frog calling at the boundary of a rice paddy

in the chorus of male Japanese tree frogs; that is, over a longer time-scale than anti-phase synchronization, male Japanese tree frogs collectively switch between a calling state and a silent state [4], which is a quite interesting phenomenon, possibly applicable to the energy-efficient information network control methods.

For development of mathematical models of such calling behavior of frogs, we need to automatically get more data on communication behavior among frogs calling in outdoor areas. For that purpose, it is necessary to determine *which* frog is in the calling state and, *which* frog is not in the calling state, i.e., in the silent state. That is, we need to know *when* and *where* individuals interact with each other. The *when* can be obtained from recorded sounds using sound separation techniques such as independent component analysis (ICA); however, it is difficult to locate frogs in an outdoor environment because they are typically small and able to conceal themselves.

For resolving the *where* problem, it is true that many sound-source localization methods have been proposed, but the majority exhibit several limitations, when applied to outdoor areas such as our field experiments [5], [6], [7], [8]. Our typical case of experiments is shown in Figure 2. Frogs are distributed in the field, but the placement area of microphones

Fig. 2. Photograph of a rice paddy where we did experiments

is limited. On the other hand, existing methods assume that the sound sources are surrounded by microphones, which requires the sound-observable range of the microphones to exceed the maximum distance between the microphones. However, this assumption is typically unavailable in an outdoor setting. Moreover, because the deployable space for system equipment is very limited in the outdoor environment, it may be difficult to locate the devices in their optimal positions.

In this study, we propose and implement a direction-of-arrival (DOA)-based sound-source localization method. In order to overcome the aforementioned limitations, our proposed method allocates microphones closer to each other than previous methods; e.g., on the four corners of a square with sides measuring 100 cm side length. The method then estimates locations outside the area surrounded by the microphones.

We implement a localization system with wireless devices connecting with a microphone to reduce the deployment cost. This brings advantages that time synchronization is easy and that the installation of devices can be flexibly changed. Besides, by locating the microphones near to each other, our method has three significant advantages: (1) it can accurately measure the positions of installed microphones, (2) it can capture the majority of generated sounds with all microphones, which is a key requirement of sound-source localization methods, and (3) the system equipment requires less space for deployment.

Reference [9] introduces wireless acoustic sensor networks (WASNs) and their application capability in acoustic monitoring and the authors of [10] propose the sound-source localization method for WASNs. In this method, a recursive algorithm for reducing the computational cost is adopted. However, when the sound source is outside the area surrounded by the microphones, the position estimation accuracy is lower compared with the one without the recursive algorithm. Of course without the recursive algorithm, the calculation time increases. We extend this method for identifying the location of sound sources outside the area surrounded by the microphones with less computational complexity while obtaining high level of accuracy. We last note that our proposed method can be used in other applications, such as robot audition, automatic meeting processing, and sound-source tracking, but it is especially useful in the outdoor sound monitoring applications where the device-installation has various restriction [11].

The remainder of this paper is organized as follows. In Section II, we describe the sound-source localization method. The estimation accuracy of our method is evaluated in Section III and Section IV presents the results of outdoor experiments. Finally, we present our conclusions in Section V.

II. Grid-based localization in the outdoor environment

A. Grid-based Localization Method

The method of [10] divides an area into N equal-sized cells. The cell whose direction from the microphones most closely matches the estimated DOA is then identified. The localization algorithm is as follows:

1) Discretize the area of interest into N cells and calculate the coordinates of the center of each cell.
2) Calculate the $(M \times N)$ matrix $\mathbf{\Psi}$ whose elements $\psi_{m,n}$ give the angle from the mth microphone array to the nth cell center (M is the number of microphone arrays).
3) Define a cost function $Cost$ that represents the degree of coincidence between the true DOA and the calculated angle in (1)

$$Cost(n) = \sum_{m=1}^{M} \left[A\left(\hat{\theta}_m, \psi_{m,n}\right) \right]^2 \tag{1}$$

where $\hat{\theta}_m$ is the DOA obtained from the mth sensor node.
4) Find the cell that minimizes the cost function, that is, $n^* = \arg\min Cost(n)$.

$A(X,Y)$ is the angular distance between X and Y. This is given by

$$A(X,Y) = 2\sin^{-1}\frac{|\exp(jX) - \exp(jY)|}{2}. \tag{2}$$

In this method, the resolution of the grid, which depends on the number of cells, N, affects the estimation accuracy. Increasing N will decrease the estimation error but increase the computational cost. Therefore, the authors of [10] proposed a recursive search method for the cell that has minimum $Cost$.

This localization method can deal with multiple sources given the correct number of sound sources. To determine the positions of multiple sources, the authors of [10] used a two-step procedure. First, the set Q containing all possible combinations of DOAs is calculated. Second, for each cell, $Cost$ is calculated using a combination of DOAs, denoted by q ($q \in Q$). The S cells that have the sth minimum $Cost$ are selected as the source locations ($s = 1, 2, \cdots, S$), where S is the highest number of DOAs detected by all microphones.

B. Extension of method to outdoor localization

Here, we describe the extension of the grid-based method proposed in [10]. When we use the original grid-based localization method to estimate the positions of sound sources outside the area surrounded by the microphone arrays, a much higher grid resolution is required to avoid the estimation error. However, this involves a greater computational cost, which results in a longer calculation time. With the recursive method proposed in [10], although the calculation time can be reduced, the estimation accuracy might decrease. In our method, we first calculate a directional cost, $Cost_d$, for each direction from the center of the microphone arrays. Then, the direction that has the minimum $Cost_d$ can be obtained. The localization server calculates the $Cost$ defined by Eq.(1) for each cell whose center is close to the line running from the center of the

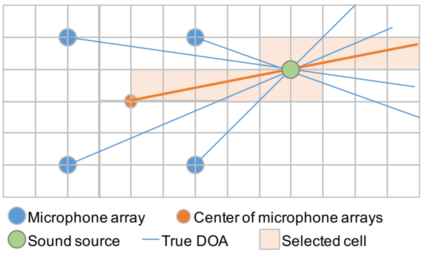

Fig. 3. Schematic showing the method for reducing the number of cells to be searched

microphone arrays according to this direction. In the following, we describe the proposed method for an example with only one sound source.

Our proposed method is divided into two steps. First, we estimate the direction in which the sound source exists and then we perform grid-based sound-source localization.

Let $\hat{\boldsymbol{\theta}}$ be an $M \times 1$ vector in which each element $\hat{\theta}_m$ is the DOA estimated by the microphone array m. Here, without loss of generality, we can assume that the coordinates of the center of the microphone arrays describe the origin. First, we estimate the direction from the origin to the sound source. To estimate the sound-source direction, we use the sum of the angular distances between a vector from the origin to the direction θ_s and the estimated DOAs of each sensor node. This is because incorrect cells in the grid-based localization for an outside area surrounded by a microphone array often have the same direction from the origin as the true cell.

The cost of the sound-source direction for each θ_s ($0 \leq \theta_s < 2\pi$) is

$$Cost_d(\theta_s) = \sum_{m=1}^{M} \left[A\left(\hat{\theta}_m, \theta_s\right) \right]^2 \tag{3}$$

where $A(X, Y)$ is the angular distance defined in (2).

Then, we can estimate the direction of the sound source as follows:

$$\theta^* = \arg\min_{\theta_s} (Cost_d(\theta_s)). \tag{4}$$

For the second step, the grid-based sound-source estimation is conducted. We start by dividing the area of interest into cells with side lengths of x; sets of cells are denoted as $\boldsymbol{P}$. The value of x affects the accuracy and computational cost of our method and is adjusted to meet the required estimation accuracy. Next, we determine the cell set $\boldsymbol{P}'$ that intersects with a vector whose starting point is the origin and whose direction is θ^* (Fig. 3). Accordingly, the computation cost of our proposed algorithm is $\mathcal{O}(\sqrt{N})$, while that of the original grid-based method is $\mathcal{O}(N)$ (or $\mathcal{O}(\log(N))$ if the above mentioned recursive approach is used). Reducing the computational cost is important for localizing multiple sound sources because, in most techniques, this requires repeating the calculation of single sound source localization.

We use the angular distance function (2) to obtain the cost in each direction. To obtain θ^* using an algorithm, we discretize θ_s by equally dividing the angle of 2π by N_θ. To achieve high accuracy, we must divide θ_s finite, which increases the computational cost. Therefore, we use a recursive algorithm.

TABLE I
SIMULATION PARAMETERS

Parameters	Value	Description
N	100×100 1000×1000	Number of cells
M	4	Number of microphone arrays
N_θ	$360/0.05$	θ_s resolution

First, we start with a coarse angle then obtain θ_1 and θ_2, which are the minimum and next-lowest $Cost_d$ values, respectively. Once θ_1 and θ_2 have been determined, we repeat this step in the range $\theta_1 \leq \theta_s \leq \theta_2$ (here, we assume that $\theta_1 < \theta_2$). This results in the desired direction and also reduces the search cost.

III. Simulation Analysis of Localization Accuracy

In this section, we evaluate the estimation accuracy of the proposed method by comparing it with the original grid-based method with and without a recursive approach using a computer simulation for clarifying the characteristics of our method. The estimation accuracy is defined as the localization error that reflects the distance between the true and estimated positions of a sound source. In the simulation, we also consider the case where a DOA error occurs. We summarize the simulation parameters of the evaluation in Table I.

In the simulation, the observation area is an $A \times A$ square and the corners of the area are assigned the coordinates $(0, 0)$, $(0, A)$, (A, A), and $(A, 0)$. Here, we set A as 10 m. This area is divided into N square cells; that is, each cell is a square with sides measuring $A/\sqrt{N}$. A sound source is randomly placed in the observation area according to a uniform distribution. Microphone arrays are placed at $(-1, -1)$, $(-1, 0)$, $(0, 0)$, and $(0, -1)$. In the grid-based method with a recursive approach, the observation area was divided into 2×2 square cells, and the search was performed recursively until the side length of the cell became less than $A/\sqrt{N}$.

We assume that the DOA error follows the same uniform distribution regardless of the distance between the microphone array and the sound source when the microphone array can obtain a sufficient SNR. This assumption is based on our actual outdoor measurements. Note that, in the DOA estimation method, an estimated DOA is chosen from predefined discrete angles [12]. Therefore, we assume that a DOA error of m, denoted by e_m^{DOA}, follows the discrete uniform distribution whose probability density function $P(e_m^{DOA} = k)$ is $1/(e_{DOA} + 1)$, where $k = 0, 1, \cdots, e_{DOA}$.

A. Simulation Results

First, we present the estimation accuracy of our proposed method without DOA errors in Fig. 4 and Table II. In the figure, we show the cumulative distribution function (CDF) of the estimation error in the proposed method (red line), the original grid-based method (blue line) and the grid-based method with a recursive approach (green line) when $N = 100 \times 100$. Since there is no significant difference between the results of $N = 100 \times 100$ and $N = 1000 \times 1000$, we only show the figure of the former result.

The localization accuracy of the proposed method was the same as that of the original grid-based method for both average and maximum error, and it was shown that the localization

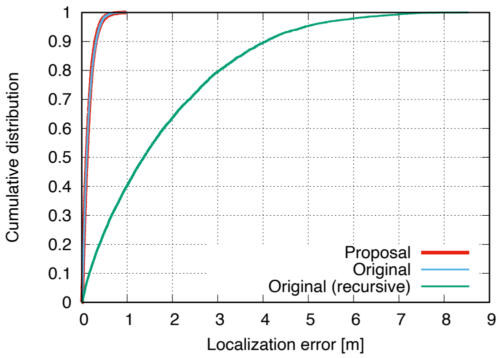

Fig. 4. Localization-error distribution without DOA errors

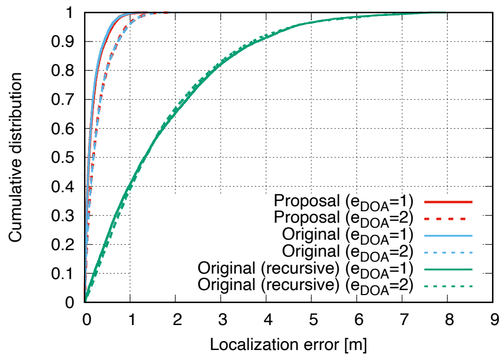

Fig. 5. Localization-error distribution including DOA errors

TABLE II
LOCALIZATION ERROR WITHOUT A DOA ERROR

	N	Error (m) Average	Error (m) Max
Original	100×100	0.142	1.007
	1000×1000	0.092	0.652
Original (recursive)	100×100	1.790	8.538
	1000×1000	1.763	8.330
Proposed	100×100	0.141	0.987
	1000×1000	0.093	0.636

can be performed with a higher accuracy than the grid-based method with a recursive approach. In the grid-based method with a recursive approach, when the size of grid division is rough, the sound source does not necessarily belong to the cell with the minimum $Cost$. Thus, although the computation cost is smaller than that of the original one, the localization accuracy becomes lower.

Next, we evaluate the localization error by considering DOA errors. We set e_{DOA} to 1 and 2.

Figure 5 and Table III show the results of simulating DOA errors. Our proposal showed almost the same accuracy as that of the original grid-based method. And both of the methods are superior to the recursive method in terms of the localization accuracy. Note that in all methods, the localization error increases when the DOA error was given, but the proposed method showed slightly better performance than that of the original grid-based method.

As shown in Section II, the computation cost of our proposed algorithm, the original grid-based method, and the grid-based method with a recursive approach are $\mathcal{O}(\sqrt{N})$, $\mathcal{O}(N)$, and $\mathcal{O}(\log(N))$, respectively. Here, the calculation time on the Laptop PC used for the localization of one sound source is evaluated. Table IV shows the average calculation time of these methods when changing the value of N. As shown in Table IV, when $N = 10,000$, there is almost no difference in the calculation time among the three methods, but when $N = 1,000,000$, the original method takes about 0.4 s for localization. In the case of multiple sound-source localization, as the number of DOA combinations increases, the calculation time for localizing them increases. Then, it can be said that our proposed method is more advantageous than the original from the viewpoint of localization accuracy and calculation time.

TABLE III
LOCALIZATION ERROR INCLUDING A DOA ERROR

	N	e_{DOA}	Average error (m)	RMSE
Original	100×100	1	0.163	0.404
		2	0.293	0.541
	1000×1000	1	0.252	0.71
		2	0.399	0.632
Original (recursive)	100×100	1	1.716	1.310
		2	1.715	1.309
	1000×1000	1	1.687	1.299
		2	1.670	1.292
Proposal	100×100	1	0.168	0.410
		2	0.291	0.539
	1000×1000	1	0.157	0.397
		2	0.288	0.537

TABLE IV
CALCULATION TIME

	$N = 100^2$	$N = 500^2$	$N = 1000^2$
Original	0.039 s	0.124 s	0.379 s
Original (recursive)	0.038 s	0.036 s	0.038 s
Proposal	0.038 s	0.037 s	0.038 s

IV. OUTDOOR EXPERIMENT

This section presents the experimental results of the proposed method conducted in an outdoor open area. We conducted outdoor experiments to clarify what performance can be achieved compared to the ideal performance obtained in the previous section.

A. Devices

First, we describe the devices used in our experiments. To obtain the DOA of the sound source, we use an 8-channel microphone array with a height of 12 cm (TAMAGO-03, System in Frontier Inc. [13]). Each TAMAGO-03 is connected to a Raspberry Pi 3 Model B with a USB cable (Fig. 6), on which we implemented the MUSIC [12] method to calculate the DOA. The TAMAGO-03 digitally converts an analog sound signal as 24-bit amplitude information at a sampling frequency of 16 kHz. The Raspberry Pi is equipped with a wireless LAN adapter (IEEE 802.11b/g/n) as standard. In the experiment, all Raspberry Pis are wirelessly connected with each other, constituting an IEEE 802.11 ad-hoc network. Sound-source localization is conducted on a laptop computer that collects DOAs from all Raspberry Pis; thus, the lap-top also belongs to the ad-hoc network. Table V summarizes the specifications of these devices.

Fig. 6. Raspberry Pi 3 Model B with an 8-channel microphone array (TAMAGO-03)

TABLE V
SPECIFICATION OF DEVICES

	Raspberry Pi 3	Laptop PC
Clock frequency	1.2 GHz, 4 core	1.9 GHz, 2 core
RAM	1 GB	8 GB
OS	Raspbian stretch	Windows 7

B. Implementation

By connecting the microphone arrays with each other by wireless communication, it is easy to place and carry the devices. Localization is conducted according to the following steps.

1) Time synchronization of Raspberry Pis and the laptop PC is performed by using the network time protocol (ntp) via wireless communication.
2) Each Raspberry Pi records 8-ch sound data received from a connected microphone array for T s.
3) Each Raspberry Pi divides the sound data into Δ s and estimates a DOA for Δ-second sound data.
4) Each Raspberry Pi transmits the estimated DOAs to the laptop PC.
5) The laptop PC conducts the proposed grid-based localization method utilizing the received DOAs.

All programs for estimating the DOA and sound-source position are written in C++ language. As mentioned above, DOAs are estimated using the MUSIC method. We set Δ to 0.5 so that it is long enough to record the bout length of a Japanese tree frog of about 0.2 s. For avoiding the influence of a temporal noise, we set T to 30 and each Raspberry Pi calculates the mode of generated DOA estimates. Note that if Δ-s sound data has a very low sound pressure level, the Raspberry Pi ignores the data and does not conduct DOA estimation. We used the squared amplitude of the recorded sound as the threshold.

To estimate a DOA by the MUSIC method, an array manifold matrix is required, which most closely fits the signal subspace of a microphone array. The array manifold matrix of TAMAGO-03 is provided by *HARK open source robot audition software* [14]. The DOA estimation resolution is 5° when using the original array manifold matrix obtained from [14]. We use an interpolation method proposed in [15], which can interpolate the array manifold matrix to any degree in the time domain and frequency domain. According to this interpolation method, the Raspberry Pi estimates the DOA to an accuracy of 1°. Note that a higher interpolation resolution increases the size of the array manifold matrix file.

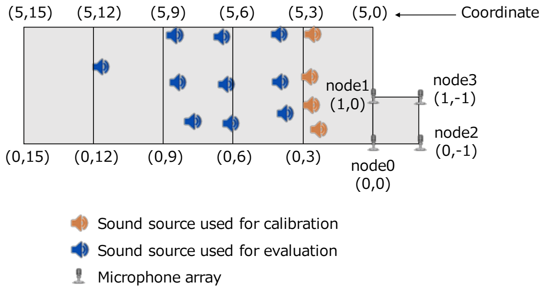

Fig. 7. Position of sound sources and microphone arrays

C. Experimental Results

In order to evaluate the accuracy of our localization system, we conducted localization experiments in an outdoor area with no obstacles near the sound source or devices. The true positions of the sound source had to be obtained in advance; however, it is difficult to measure their accurate positions in an outdoor environment. Therefore, we used a laser distance meter with an error of approximately 1 mm (Leica DISTO D210 [16]) and calculated the positions of the sound source by triangulation. It was also necessary to calibrate the direction of the microphone arrays in advance, using several localization results. According to the results from section III, localization accuracy is higher when the sound source is located near to the microphone arrays; therefore, for the calibration, we installed the sound source close to the microphone arrays.

We installed microphone arrays as shown in Fig. 7. For the sound source, we used a loud speaker that replayed the advertisement calls of a Japanese tree frog. The maximum sound pressure level of the replay was approximately about 80 dB. The localization parameters were the same as those in the simulation shown in Table I.

We show the results in Table VI. The average, maximum, and minimum values of the localization error are 0.57 m, 1.28 m, and 0.16 m, respectively. Note that when we can obtain the true DOA estimates, these values are 0.13 m, 0.38 m, and 0.06 m, respectively. Regarding computational time, DOA estimation takes approximately 0.07 s for a 0.5-s 8-ch sound data and location estimation takes approximately 0.1 s.

In the experiment, the estimated DOAs include an average error of 1.8° and a maximum error of 4°. These errors are caused by various factors, such as sound reverberation, the position error of the microphone arrays, and the sound source. Specifically, the Raspberry Pi connected to the microphone array has a strong influence on the DOA estimation error, likely due to sound reflection. For more accurate localization, increasing the number of microphone arrays is a simple and robust solution. This is easily achieved because they are connected by wireless communication.

V. CONCLUSION

In this study, we proposed a sound-source localization method using a wireless microphone-array network for the outdoor environment. There is a possibility that the deployable space for system equipment is very limited in an outdoor environment. Then, the proposed method allocates microphone arrays close to each other, which also reduces the position

TABLE VI
RESULT OF LOCALIZATION EXPERIMENT

Position of sound source		Estimated result		Localization error (m)
x	y	x	y	
0.31	4.01	0.425	4.125	0.16
2.34	3.98	2.475	4.875	0.91
3.71	3.76	3.325	3.675	0.40
0.40	6.48	0.575	6.075	0.45
2.46	6.30	2.325	6.225	0.15
4.13	6.08	3.925	6.225	0.25
0.36	8.50	0.525	8.325	0.24
2.37	8.38	2.125	7.475	0.98
4.05	7.73	4.125	8.625	0.90
1.72	11.70	1.775	10.425	1.28

error of the microphone arrays, and estimates the location of a sound source for an outside area surrounded by them. Simulation results showed that the proposed method can estimate the position of a sound source with an average error of 0.29 m for a 10 m $\times$ 10 m area when errors related to the DOA estimation were considered. At the same time, it can reduce the calculation time by 90% compared with a grid-base localization method. Therefore, the method provides novel advantages without significantly reducing the accuracy of the original grid-based method. However, the method suffers from a low estimation accuracy with increasing DOA errors as we showed in outdoor experiments. In the experiments, the average localization error of our proposed method was 0.57 m. In order to improve the localization accuracy, it is necessary to improve DOA estimation, and also it is effective to use more microphone arrays and to appropriately determine their installation position. Furthermore, it is essential to realize the localization of multiple sound sources. These are our future work.

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