SENSOR NETWORKS FOR ACOUSTIC SOURCE LOCALIZATION USING ACOUSTIC FINGERPRINT IN URBAN ENVIRONMENTS AND CONSTRUCTION SITES

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ABSTRACT: We investigate the feasibility and performance of the acoustic localization system using the acoustic fingerprint for asynchronous wireless sensor network (WSN) in urban environments and construction sites. The location estimation is calculated by comparing the acoustic fingerprint obtained from multiple sensors with those pre-computed in the database. To calculate the fingerprint, we avoid expensive measurement process by using a 2-dimensional finite-difference time-domain (FDTD) to approximate acoustic propagation in urban area. The implementation cost for constructing the acoustic fingerprint map using FDTD is small compared to that of the exhaustive data measurements over an entire test site. We select the direction-of-arrival (DoA) of the first arrival path of the acoustic signal as a location fingerprint to avoid complexity from synchronization. The fingerprint from each node is weighted by the measured amplitude of the received acoustic waveform to take into account the decrease in the amplitude due to the distance between the source and the sensor node. We test our proposed localization algorithm at the 140x80 m^2 artificial village area used for military drills. With proper node placement, our proposed algorithm can achieve strong localization performance using small number of sensor nodes. In particular, the root-mean-square-error (RMSE) between the estimated and accurate source position is 6.30 meters using observations from only 3 sensor nodes. Our proposed algorithm exhibits robustness to DoA estimation error representing the cumulative effect of uncertainties in urban environments and construction sites.

Keywords: *Surveillance, Monitoring, Acoustic source localization, Wireless sensor network, Fingerprinting*

1. INTRODUCTION

Wireless sensor networks (WSNs) in acoustic-related location-based services has gained widespread applications in urban environments and construction sites such as acoustic tracking system [1], noise monitoring and mitigation and counter-sniper systems [2]. Typically, multiple acoustic sensors forming a distributed sensor network are used where observations from the sensors are processed, transmitted and fused at the coordinator to estimate the sources' location. However, acoustic source localization (ASL) in urban environments is difficult due to multi-path effect including, non-line-of-sight (NLOS), multi-path propagations, reflections, diffraction and scattering by surrounding buildings. Existing systems [1,2], operating in synchronous mode, localize the acoustic source by exploiting time-of-arrival (ToA) of the observations assuming LoS between majority of the sensors and the target which might not be achieved in urban environments. Their system performance degrades significantly in the environments with large reverberation time especially in NLOS situations. In particular, reverberation distorts the energy while NLOS situations obstruct the sensors from obtaining ToA of the direct arrival path. Without proper system adjustment, localization error due to NLOS can dramatically degrade the system performance [3].

Few papers address NLOS problems in ASL. [3] and [4] proposed matched-field processing (MFP) and time-reversal process to estimate the acoustic source's coordinate using accurate acoustic propagation modeling. To model outdoor acoustic propagation in the city, finite-difference time domain (FDTD) has been widely used to approximate a solution of acoustic wave propagation equation characterized by a set of first-order velocity-pressure coupled differential equations. Reflections and diffraction on objects such as trees and buildings can be easily implemented with FDTD and exhibits good agreement with the measure waveform [4]. However, both methods rely on the accuracy of the acoustic propagation model and suffer heavily from model mismatch.

WSN for indoor localization using radio frequency (RF) overcomes multi-path and NLOS effects through fingerprinting [5]. RF fingerprinting usually consists of two phases. First, the system relates RF propagation parameters (fingerprint) to every training point and stores them in the database. In phase two, the system calculates the fingerprint obtained from sensors and finds the best matching entry from the database. RF fingerprinting effectively solves NLOS situations since the propagation parameters of the direct path are not required. Performance depends on the type of the fingerprint, grid size during the training step and dynamics of the environments. Despite widespread applications of RF fingerprinting for indoor localization, no paper has considered applying the fingerprint concept for asynchronous WSN-based ASL problem in urban environments.

In this paper, inspired by the RF fingerprint, we propose the acoustic fingerprinting for ASL using asynchronous WSN in urban environments. The location estimation is calculated by comparing the acoustic fingerprint obtained from multiple sensors with those pre-computed in the database. We calculate the fingerprint using a 2-dimensional FDTD to approximate acoustic propagation in urban area. The implementation cost for constructing the acoustic fingerprint map using FDTD is small compared to that of the exhaustive data measurements over an entire test site. We use direction-of-arrival (DoA) of the first arrival path of the acoustic signal as a location fingerprint to avoid any additional complexity from synchronization. The fingerprint from each node is weighted by the amplitude of the first arrival path. This takes into account the decrease in the amplitude due to the distance between the source and the sensor node. Both amplitude and phase of the first path can be extracted with low complexity processing hardware and transmitted using low communication bandwidth. We test our proposed ASL system at the 140x80 m^2 artificial village area used for military drills. Real gunshots are fired at various locations in the test site to test the performance of our system. We compare the performance of our system in terms of the root-mean-square-error (RMSE) between the true and estimated source positions with a widely-used bearing crossing source localization. Moreover, there are several unavoidable uncertainties in urban environments including the exact position of the scatterers and fluctuations in the density of the mediums or temperature. This randomness leads to several modeling mismatched which could severely impact the performance of the acoustic fingerprinting. We model the cumulative uncertainty effect as the uncertainties in the phase of the propagating wave which can be represented by the additive white Gaussian noise [6] contributing to the DoA estimation error. Its impact on the robustness of the performance of the proposed ASL system will be investigated.

We focus on 2-D localization although extension to 3-D is straightforward. This paper is organized as follows. In Section 2 describes FDTD approximation of the acoustic propagation in urban environments. We discuss the acoustic fingerprinting algorithm in Section 3. In Section 4, performance analysis of the proposed system is studied under uncertainties in urban environments. Section 5 concludes this paper.

2. FDTD APPROXIMATION OF THE ACOUSTIC PROPAGATION IN URBAN ENVIRONMENTS

2.1 Test environment

The test environment is a 140x80 m^2 artificial training village whose model is shown in Fig. 1. Fig. 2 shows a photographic view at the village taken from Building B toward North-East direction. Due to several buildings scattered around the area, acoustic propagation in this area will be affected by multipath propagations creating challenging situations for the sensor network to locate the acoustic source. Our ASL system consists of a sparsely deployed sensor network and a central node which are unsynchronized to each other. Each sensor possesses limited local processing capability and small communication bandwidth and is equipped to a microphone array. The microphone array is made up of 3 microphones forming a symmetrical triangle with a separation of 52 cm from each other. Every microphone inside a sensor node is synchronized with each other. Extracted information from the sensors are transmitted and fused at the central node to estimate the acoustic source.

2.2. 2-dimensional FDTD approximation

FDTD method [4] is a numerical technique widely used for analyzing electromagnetic problems. The analysis domain of space and time is divided into small unit cells and the partial derivative equations are approximated using central-difference approximation. We approximate acoustic propagation in urban environment using 2-dimensional FDTD computation due to its accuracy to model the propagation with low computational complexity [4]. From geographic information of the artificial village, we come up with a 2-dimensional FDTD approximation model as presented in Fig. 3. Snapshots of the simulated acoustic wave when the source is at (40, 10) are presented. FDTD cell size is 0.1x0.1 m^2. The total number of cells is 112,000 which is approximately 35 cells per primary wavelength. Time step is 0.022 ms and the source pulse is the blast pulse wave with center frequency at 100 Hz. Simulation time is 0.5s. Any disagreements between the observations and those generated by FDTD will be treated as an error due to model mismatch.

3. THE ACOUSTIC FINGERPRINT LOCALIZATION

We obtain location-associated acoustic fingerprints from FDTD simulation as described in Section 3. We consider DoA of the first arrival path as our acoustic fingerprint since no timing information is needed across the sensor network. We obtain the fingerprint associated with each source location (grid point) by analyzing the DoA at every sensor using FDTD computation. This will be pre-computed and stored in the database. During the field test,

Fig. 1 A model of an artificial village consisting of 17 concrete-block buildings (marked by alphabet A to S) and Sensor 1 to 4 (marked by stars). The roads are asphault and the light ground areas are packed pebble. Building B has 3 stories; others are 1 or 2 stories tall.

Fig. 2 A photograph of the artificial village taken from building B pointing toward North-East direction. Building D is on the left with 7/11 banner. Sensor 2 is on the right in front of Building E. Building I is at the center beyond Building D and E.

real gunshots were fired from 9mm pistols at various locations in the artificial village. The processing unit inside every sensor node estimates the DoA of the first arrival path using a standard 2-step Time-difference-of-arrival (TDoA) algorithm. Although we assumes far field and narrow band assumptions which might not be hold in all observations in this experiment, these approximations can be applied with acceptable errors in many cases [6]. Both DoA and amplitude of the first arrival path are sent to the central node. At the central node, the distance between the observation $\hat{\theta}_i$ from the ith sensor node and the fingerprint from a source position *(x,y,)*, $\theta_i(x,y)$, is

$$D_i(x,y) = \left|\hat{\theta}_i - \theta_i(x,y)\right|^2. \quad (1)$$

We take into account the distance factor between the source and every sensor node using the measured amplitude $\hat{A}_i$ as a weighting coefficient. As the distance between the source and sensor increases, small DoA mismatch could result in severe location estimation error. Hence, the cost function taking into account fingerprinting from every node can be written as

$$D(x,y) = \sum_{i=1}^{N} w_i D_i(x,y) \quad (2)$$

where N is the number of sensor nodes used and $w_i = \hat{A}_i / \sum_{j=1}^{N} \hat{A}_j$ is the weighting factor of the *i*th node. Finally, the coordinate with smallest Euclidean distance is selected as the most likely source location, i.e.,

$$(\hat{x}, \hat{y}) = \min D(x,y). \quad (3)$$

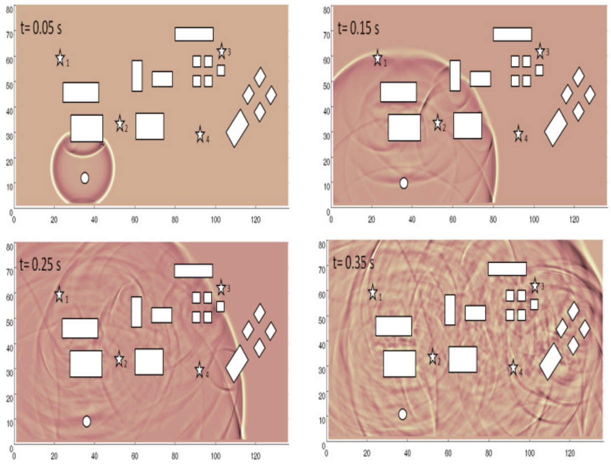

Fig. 3 2-dimensional FDTD model of the test site. Sensor 1 to 4 are marked by stars. Snapshots of the simulated acoustic wave when the source is at (40, 10) are presented at times t=0.05, 0.15, 0.25 and 0.35s.

4. EXPERIMENTS AND DISCUSSIONS

We test our algorithm at the artificial village. To construct the acoustic fingerprint, we choose a fingerprint grid size of 4 meters and a total of 35x20 acoustic fingerprints are specified over the test site as shown in Fig. 1. The measurements were conducted in November 2010 with temperatures ranging from 25-30 °C, wind speeds around 5 m/s. Under these weather conditions, the sound speed ranges from 346.12 to 349.0 m/s. During the experiment, more than 100 shots of 9 mm pistol are fired over different spots in the artificial village. Performance of the localization system is evaluated over several combination of sensor nodes deployed at the spot 1 to 4 as shown in Fig. 1. We compare our performance with the bearing crossing method in terms of the RMSE value.

1) Localization performance analysis

We test our algorithm using 2, 3 and 4 sensor nodes for ASL where all combinations of node configuration are tested. Fig. 4 plots the cost function D(x,y) (Eq. 2) when Sensor 1,2 and 3 are used. Due to multi-path propagation, the estimate DoAs at Sensor 1, 2 and 3 are shifted resulting in the crossing of the bearings at (10.2, 39.4), 41.8 meter from the true source position which is at (40, 10). However, our proposed method estimates the source position at (36.5, 6.4), only 5.02 meter from the true position. Table 1 summarizes the localization performance over several combination of sensor nodes used for localization. In particular, the first row of Table 1 uses observations from Sensor 1 and 2 to estimate the acoustic source position. These results can approximately describe which locations are the best positions to place the sensor. From Table 1, our proposed ASL method (acoustic fingerprint) shows improved localization performance as the number of nodes increases. The error could come from model mismatch due to FDTD computations or some unavoidable uncertainties in the urban environment during the experiment. Accuracy around 10 m. in space is acceptable since the system can locate the source within an area or building. Also, a combination of the observations from sensor 1, 2 and 4 outperforms those using 4 sensors nodes. This could be an interesting point for future study on how the geographic information impacts the localization performance. From Table 2, the average RMSE is 12.86, 10.50 and 7.92 meters when 2, 3 and 4 sensor nodes are used, respectively. Our proposed fingerprint method outperforms that of the bearing crossing for any combination of sensors used. Nevertheless, the superiority of our proposed algorithm over the bearing

Configuration	Acoustic fingerprint	Bearing crossing*
Sensor 1, 2	12.59	33.14
Sensor 1, 3	15.99	27.79
Sensor 1, 4	**8.87**	**19.25**
Sensor 2, 3	12.11	26.58
Sensor 2, 4	11.77	23.39
Sensor 3, 4	14.62	21.26
Sensor 1, 2, 3	9.78	27.46
Sensor 1, 2, 4	**6.30**	**14.37**
Sensor 2, 3, 4	11.52	14.06
Sensor 1,2,3,4	**7.92**	**10.73**

Table 1 Average localization RMSE (meters) of the proposed fingerprint and the bearing crossing methods. (*RMSE greater than 100 m are not included.)

Number of sensor nodes	Acoustic fingerprint	Bearing crossing
2	12.86	25.35
3	10.50	17.84
4	7.92	10.73

Table 2 Average localization RMSE error (meters).

crossing method decreases as the number of sensor nodes increases. From Table 2, the RMSE of the bearing crossing method is 1.97 (25.35/12.86) times higher than that of the acoustic fingerprint when only 2 sensors are used. However, with 4 sensor nodes, RMSE of the bearing crossing is reduced to 1.35 (10.73/7.92) times higher than that of the acoustic fingerprint. This is due to the fact that more information is available as the number of nodes increases so that the bearing crossing method can exploit to improve its performance. This shows that with proper sensor placement, our proposed algorithm achieves strong localization performance when a few number of sensor nodes are used.

2) Robustness to uncertainties affecting DoA estimation

We model the cumulative effect of the uncertainties

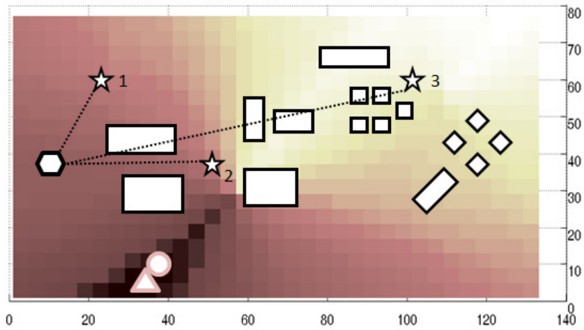

Fig. 4 The cost function D(x,y) (Eq. 2) when Sensor 1, 2 and 3 are used. The true source position is at (40, 10) (marked by O). The estimate source position using the proposed method is at (36.5, 6.4) (marked by Δ) while the bearing crossing method estimates the source location at (10.2, 39.4) (marked by ⬡)

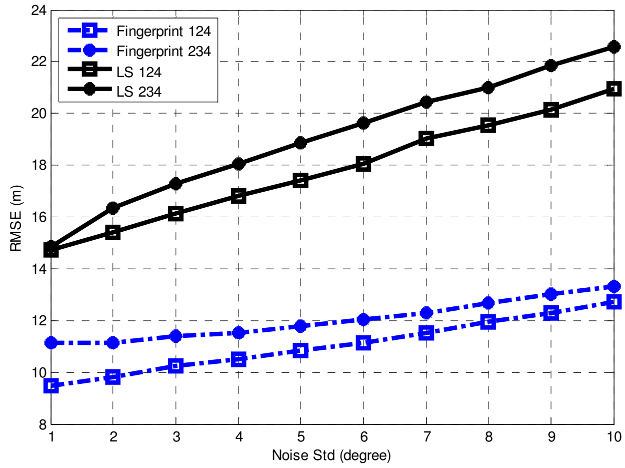

Fig. 5 Impact of DoA estimation error on the localization in terms of RMSE (meters).

contributing to DoA estimation error by zero-mean Gaussian random variables whose standard deviation (std) parameterizes severity of the uncertainties. We assume the random noise corrupted each sensor node are independent and identically distributed (i.i.d.). We parameterize the noise std from 1 degree to 10 degree. 2000 realizations are generated for each std. The results are presented in Fig. 5 in terms of the average localization RMSE error over a range of noise std. We consider the performance when only observations from

3 sensor nodes are used. From Fig. 5, legend 'Fingerprint 234' and 'LS 234' mean the performance of our proposed algorithm and bearing crossing method using observations from Sensor 2, 3 and 4, respectively. Our method shows stronger robustness to the DoA estimation error than the bearing crossing method. For example, for 'FDTD 234', as the noise std rises from 1 degree to 10 degree, the RMSE is increased by 2.19 m. (from 11.13 to 13.32 meters). However, for 'LS 234', the error is increased by 7.70 m. (from 14.86 to 22.56 meters). This is due to the indirect mapping characteristics of the fingerprinting concept between the observations and the source position. Because of an independent assumption of the noise on each sensor, one strong noise induced on one sensor has small impact as long as the noise components induced on other sensors are weak. In contrary, for bearing crossing method, the position estimate is at a crossing of the bearings, unless there are enough sensors with good observations, one poor observation could result in severe performance degradation as shown in Fig. 5.

5. CONCLUSIONS

We have investigated the performance of asynchronous WSN-based ASL system using acoustic fingerprint in urban environments and construction sites. The DoA of the first arrival path of the acoustic signal is selected as a location fingerprint so that the system can operate in asynchronous mode. The fingerprint is calculated using a 2-dimensional FDTD to avoid time-consuming data measurement at a test site. The fingerprint from each node is weighted by the measured amplitude of the first arrival path to take into account the decrease in the amplitude due to the distance between the source and the sensor node. We test our proposed localization algorithm at the 140x80 m^2 artificial village area used for military drills. With proper node placement, our proposed algorithm can achieve strong localization performance using small number of sensor nodes. In particular, the RMSE between the estimate and true source position is 6.30 meters using observations from only 3 sensors which is acceptable since the system can locate the source position within a certain area or a building. Also, our proposed algorithm exhibits robustness to DoA estimation error representing the cumulative effect of uncertainties in urban environments. This study provides a feasible approach for locating the acoustic source in urban environments and construction sites using asynchronous WSN based on acoustic fingerprinting algorithm. Furthermore, this could serve as a foundation for further study on acoustic tracking system, noise localization or noise mapping and mitigation in urban environments or construction sites.

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