

Location-Aware Speakers for the Virtual Reality Environments

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ABSTRACT This paper presents location-aware speakers for the immersive virtual reality environments as well as conventional surround sound systems. The surround sound system generally requires multiple speakers fixed in specific positions and connected to dedicated audio jack holes. In this paper, we propose wireless speakers that can aware their locations and dedicated sound channels without troublesome installations. The proposed speakers use the Internet of things devices by combining a Raspberry Pi and a beacon to each speaker, which enable smart and connected applications. Each speaker estimates distances to other speakers from received signal strength indication of beacons with bluetooth low energy signals. By analyzing the relative distances between speakers, we detect the speaker locations in various speaker setups. We experimented our method with three sound system formats in various sizes and analyzed the accuracy of the location detection.

INDEX TERMS 3D audio rendering, surround sound, indoor localization, received signal strength indication, internet of things, bluetooth low energy.

I. INTRODUCTION

In immersive virtual reality environments, the realistic audio rendering is also very important for the user immersion in addition to the realistic visual rendering. The three-dimensional audio rendering requires multiple surrounding speakers for reproducing the realistic sound field [1], [2]. The wired surround sound system requires an annoying installations for connecting cables between speakers and corresponding audio jack holes in the sound sources. The Internet of Things (IoT) technology enables us to convert traditional and normal devices into smart and connected devices. In this paper, we propose location-aware speakers for the wireless surround sound systems with the RSSI-based (received signal strength indication) localization. Each speaker can detect its location in a specific speaker format and play an appropriate sound channel. The proposed method enables a quick and easy installation of the surround sound system. Especially for the immersive virtual reality environments, it would be useful because it would be more frequent to relocate the projector-based immersive systems or HMD (head-mounted display) systems than to relocate conventional sound systems. The indoor and outdoor localization is a crucial technique in IoT and Wireless Sensor Networks (WSN). However, it is still difficult to find accurate locations with wireless devices.

There would be too much errors for estimating absolute locations of speakers. Therefore in this paper, we estimate relative distances between speakers and determine each speaker's position in a specific sound format. We attach a Raspberry Pi and a beacon to each speaker and estimate distances between speakers from the RSSI of beacons with Bluetooth Low Energy (BLE) signals. We show the accuracy of the proposed method in three sound system formats of the stereo sound, the 5 surround sound, and the 8 surround sound systems.

II. RELATED WORKS

There have been many research interests in indoor position estimation problems. The time of arrival (TOA) technique measures the distance using the time of arrival from multiple positions and the trilateration [3]. The time difference of arrival (TDOA) [4] has only relative time differences, and the angle of arrival (AOA) [5] uses the triangulation method with the angles of the signals [6].

The RSSI-based localization methods use the received signal strengths from wireless devices including WiFi, Zigbee, radio frequency identification (RFID), and Bluetooth [7]. The RSSI ranging methods are popular in wireless sensor networks since they require less communication overhead, lower cost and easy implementation cost [8]. Especially the

RSSI with Bluetooth low energy (BLE) has been widely used on mobile devices due to its low power consumption and low cost. Hara and Anzai [9] compared the performances of the RSSI-based and the TDOA-based location estimation methods. Xu *et al.* [8] proposed a distance estimation method by describing the relationship between the RSSI values and the distances using a log-normal shadowing model. Parameswaran *et al.* [10] evaluated the reliability of the sensor localization algorithms using RSSI. Saxena *et al.* [11] also analyzed the RSSI distance estimation method with empirical error metrics. Cheng *et al.* [12] proposed an indoor robot localization by combining RSSI and TDOA localization algorithms. They used a polynomial fitting for describing the relationship between the RSSI and the distance. Lau and Chung [13] proposed an RSSI location estimation technique for both indoor as well as outdoor environments. They also used an RSSI smoothing algorithm for more reliable estimation. Chowdhury *et al.* [14] presented an RSSI-based location estimation using smartphones. They also used the same RSSI smoothing algorithm as Lau and Chung [13]. They analyzed the performance of various models such as Linear Approximation Model, Free Space Friis Model, and Flat Earth Model and proposed a composite model with experimental data. In this paper, we use the RSSI-based distance estimation with a smoothing algorithm [13], [14] and the polynomial fitting function [12].



FIGURE 1. A speaker prototype with a beacon and a Raspberry Pi.

III. LOCATION-AWARE SPEAKERS

A. OVERVIEW

A single location-aware speaker is composed of a normal speaker, a Raspberry Pi, and a beacon. We use a Raspberry Pi 3 model B+ with a Raspbian operations system. The Fig 1 shows a prototype of our speakers. Speakers can exchange data with each other through the WiFi connections and process location detection algorithms. Moreover, it is possible to add wireless sound channel transmission.

In this paper, we use three sound system formats of the stereo, 5.1 surround, and 8 surround sound systems as shown in Fig 2. Speakers can automatically detect the current sound system format by counting the number of detected beacons. Our method automatically detect the location of each speaker by estimating the distances between speakers with RSSI from

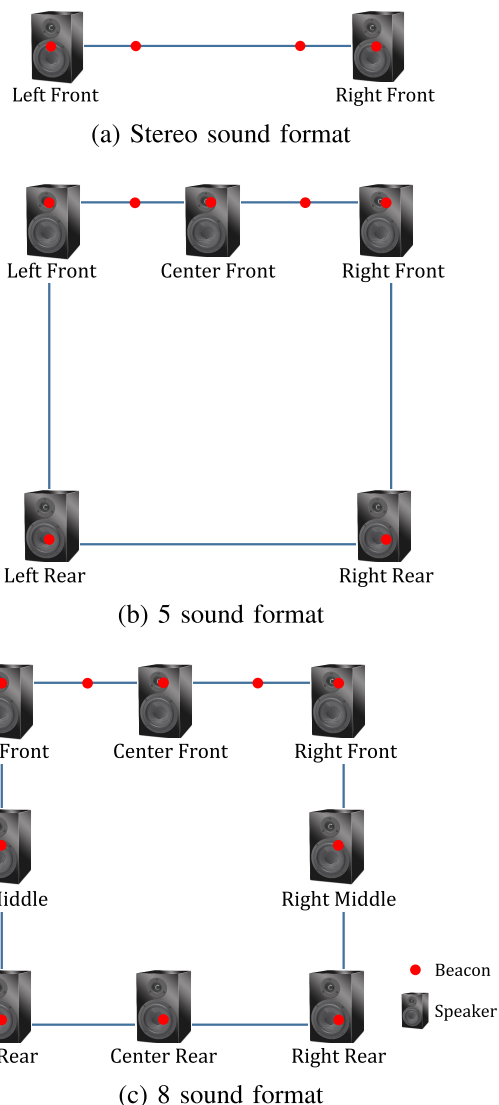


FIGURE 2. Three sound formats: (a) The stereo sound format uses only the Left Front and the Right Front speakers and (b) the 5.1 sound format uses the Left Front, Center Front, Right Front, Left Rear, and Right Rear speakers. (c) The 8 surrounding speaker format uses all 8 speakers in this figure.

other speakers. Even though we know the exact distances between speakers, we cannot determine the location of the speakers in the sound system format without any reference position. For example, in 8 sound format in Fig 2 (c), the Left Front speaker and the Right Front speaker are not distinguishable only with relative positions since the whole system can be rotated by 90 degree. To solve this problem, we add two beacons in between front speakers as shown in Fig 2. After all the speakers determine their locations, speakers can receive appropriate wireless sound channels for rendering immersive 3D audio. The wireless 3D audio rendering is a future research and is not described in this paper.

B. RSSI-BASED LOCALIZATION

For estimating the distances between speakers, we use the RSSI-based localization. The Raspberry Pi attached to the

speaker detects the strength of the received Bluetooth low energy signals from the beacons including two reference beacons as well as beacons attached to speakers. Each speaker estimates the distances to other speakers and two reference beacons by analyzing these RSSI values. To estimate distances, we first precompute the distance estimation function by sampling RSSI values at various distances and fitting a polynomial function to the RSSI-distance pairs. Then we smooth the RSSI values from other devices and estimate distances with the fitted function. By using these distances, we finally determine the location of speakers in a sound system format. The following sections describe the details of these processes.

C. SMOOTHING OF RSSI

We use an RSSI smoothing algorithm for more reliable estimation. The RSSI values are unstable and rapidly changed even in a stable distance. To alleviate this, we use an averaging and smoothing algorithm [13], [14] for getting more stable RSSI values. The smoothing algorithm first takes N RSSI values recorded in a short time and then discards both extreme values in maximum and minimum. To discard the extreme values, it sorts the N RSSI values and take middle m values which means it discards $\frac{N-m}{2}$ smallest values and $\frac{N-m}{2}$ biggest values. Now it takes the average of the middle m RSSI values for the future calculation. Each speaker continuously receives RSSI values and calculates a sequence of smoothed RSSI average values. Let i -th smoothed RSSI average value be \hat{P}_i . This set of $\{\hat{P}_i\}$ is used for fitting functions as well as estimating distances. In this paper, we use $N = 50$ and $m = 30$. The algorithm is as shown below.

- 1) Get N RSSI values
- 2) Sort the N RSSI values in increasing order
- 3) Take the middle m RSSI values from the sorted list
- 4) Take average of the m RSSI values

D. DISTANCE ESTIMATION WITH A POLYNOMIAL FITTING

For estimating distances from the RSSI values, we can model the relationship between RSSI and distance with various functions including the linear approximation model, the free space Friis model, and the log-normal shadowing model [14]. One of the most popular model is the log-normal shadowing model.

$$P(d) = P(d_0) - 10n \log\left(\frac{d}{d_0}\right) + X_0 \tag{1}$$

Where d is the distance and $P(d)$ represents the corresponding signal strength. $P(d_0)$ represents the path loss at reference distance of d_0 meters. Normally, $d_0 = 1$ and n is path loss exponent. $X_0 \sim N(0, \sigma^2)$ is the noise modeled with zero mean Gaussian with variance σ^2 . The log-normal model sometimes fails to represent the relations between the distance and the RSSI and Cheng *et al.* successfully applied a polynomial function for modeling the distance estimation [12]. In this paper, we use the polynomial

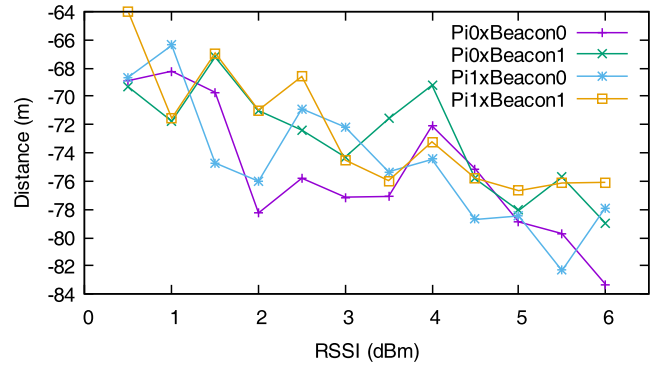


FIGURE 3. RSSI values in various distances with different Raspberry Pi and beacon pairs.

fitting for estimating the distances from the RSSI values. Cheng *et al.* [12] estimated the order of the polynomial function by finding the order which has no remarkable difference of the residual sum of squares with the higher order. In this paper, we use a cubic polynomial function. Let d be the distance and P be the RSSI value, then the function for estimating distances is as follows.

$$d = f(P) = \alpha_0 + \alpha_1 P + \alpha_2 P^2 + \alpha_3 P^3 \tag{2}$$

We take a set of RSSI-distance pairs (\hat{P}_i, d_i) for $i = 1, 2, \dots, n$ by sampling the smoothed average of RSSI values in various distances. We use the least squares method for fitting the function to the data. The Fig 3 shows RSSI values $\{\hat{P}_i\}$ in various distances with various Raspberry Pi and beacon pairs. The graph shows RSSI values of pairs of two beacons and two Raspberry Pis.

E. LOCATION ESTIMATION IN A SOUND SYSTEM FORMAT

Using the distance estimating function in Equation 2, we estimate the distances between speakers as well as between the speakers and the two reference beacons. In each speaker, it determines its location which is one of the Left Front, Center Front, Right Front, Left Middle, Right Middle, Left Rear, Center Rear, Right Rear as shown in Fig 2. We use three sound system formats. The stereo format is composed of two speakers and two reference beacons, the 5 speaker format consists of five speakers and two reference beacons, and the 8 speaker format consists of eight speakers and two reference beacons. For each format we experimented three dimensions where the lengths of the longest edges in the sound format are 2, 3, and 4 meters respectively. As shown in Fig 4, each speaker can get signals from up to nine devices. Since the distance estimation is not very accurate, we use the relative distances for determining the locations. We incrementally detect the locations. First, we detect the Center Front speaker since it is closest to both of the reference beacons. Secondly, we detect the Left Front which is closest to the left reference beacon and the Right Front which is closest to the right reference beacon. Next, we detect the Left Rear which is furthest from the Right Front, and

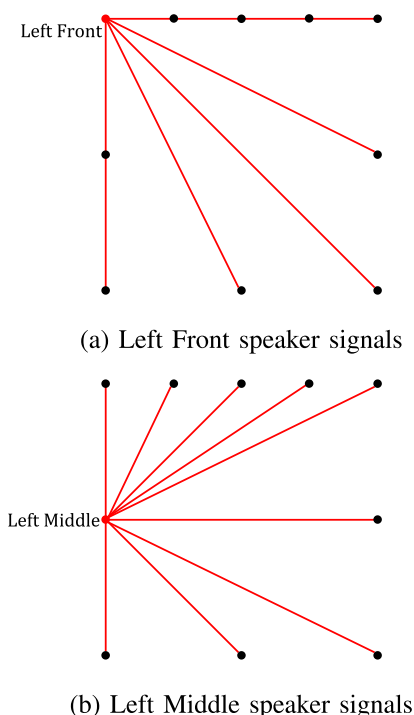


FIGURE 4. Signal transmission between eight speakers and two beacons: (a) Left Front speaker receives nine signals from other speakers and beacons, and (b) Left Middle speaker also receives nine signals.

the Right Rear which is furthest from the Left Front. Now, we detect the Left Middle which is closest to the Left Front, and the Right Middle which is closest to the Right Front. Finally, the last one is determined as the Center Rear. The algorithm is as follows.

- 1) Detect Center Front which is closest to both of the reference beacons
- 2) Detect Left Front which is closest to the left reference beacon
- 3) Detect Right Front which is closest to the right reference beacon
- 4) Detect Left Rear which is furthest from the Right Front
- 5) Detect Right Rear which is furthest from the Left Front
- 6) Detect Left Middle which is closest to the Left Front
- 7) Detect Right Middle which is closest to the Right Front
- 8) Detect the last one as Center Rear

IV. RESULTS

We executed 50 experiments for each sound format and each dimension. Table 1 and Fig 5 show the result of our system. For the small sound format whose size is 2 meters, the accuracy was low for all three sound formats. This is caused by the intrinsic error in the RSSI-based distance estimation methods. For bigger dimensions such as 3 and 4 meters, the accuracy was high enough for the practical uses. Especially, in stereo 3 and 4 meters formats and the 5 speakers 4 meter format, our method detected the locations perfectly in all experiments.

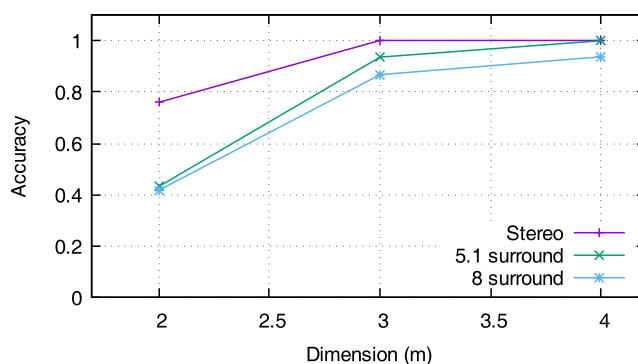


FIGURE 5. Speaker setup with a beacon and a Raspberry Pi.

TABLE 1. Accuracy of speaker location detection.

dimension (m)	Stereo	5 speakers	8 speakers
2	0.760	0.432	0.418
3	1.000	0.936	0.868
4	1.000	1.000	0.938

V. CONCLUSION

In this paper, we present location-aware speakers for automatically determining their locations in surrounding sound systems. We use a speaker combined with a Raspberry Pi and a beacon for estimating distances between speakers from the RSSI values of Bluetooth low energy signals. With estimated distances between speakers, we incrementally determine the location of speakers in the sound system format. We experimented three sound system formats in various sizes to verify the effectiveness of our method. Even though the system shows some errors in small areas because of the inaccuracy the RSSI-based distance estimation, it can successfully determine locations in larger areas.

In this paper, we only use the Bluetooth signals. If we apply a hybrid method by combining other signals such as WiFi signals or other methods such as Time Of Arrival (TOA) and Time Difference Of Arrival (TDOA) methods with ultra sound systems, the accuracy of the system could be improved. In addition, for the location detection in the sound format, we could improve the results by applying deep-learning or other artificial intelligence (AI) techniques.

REFERENCES

- [1] M. Naef, O. Staadt, and M. Gross, "Spatialized audio rendering for immersive virtual environments," in *Proc. ACM Symp. Virtual Reality Softw. Technol.*, 2002, pp. 65–72.
- [2] N. Tsingos, E. Gallo, and G. Drettakis, "Perceptual audio rendering of complex virtual environments," *ACM Trans. Graph.*, vol. 23, no. 3, pp. 249–258, 2004.
- [3] K. Yu and Y. J. Guo, "Non-line-of-sight detection based on toa and signal strength," in *Proc. IEEE 19th Int. Symp. Pers., Indoor Mobile Radio Commun.*, Sep.2008, pp. 1–5.
- [4] I. I. Kim, J. G. Lee, and C. G. Park, "A mitigation of line-of-sight by TDOA error modeling in wireless communication system," in *Proc. Int. Conf. Control, Autom. Syst.*, Oct. 2008, pp. 1601–1605.
- [5] D. Niculescu and B. Nath, "Ad hoc positioning system (APS) using AOA," in *Proc. IEEE INFOCOM*, vol. 3. Mar. 2003, pp. 1734–1743.
- [6] F. Seco, A. R. Jimenez, C. Prieto, J. Roa, and K. Koutsou, "A survey of mathematical methods for indoor localization," in *Proc. IEEE Int. Symp. Intell. Signal Process.*, Aug. 2009, pp. 1734–1743.

- [7] H.-S. Cho, J. Ji, Z. Chen, H. Park, and W. Lee, "Accurate distance estimation between things: A self-correcting approach," *Open J. Internet Things*, vol. 1, no. 2, pp. 19–27, 2015.
- [8] J. Xu, W. Liu, F. Lang, Y. Zhang, and C. Wang, "Distance measurement model based on RSSI in WSN," *Wireless Sens. Netw.*, vol. 2, no. 8, pp. 606–611, 2010.
- [9] S. Hara and D. Anzai, "Experimental performance comparison of RSSI- and TDOA-based location estimation methods," in *Proc. IEEE Veh. Technol. Conf.*, May 2008, pp. 2651–2655.
- [10] A. T. Parameswaran, M. I. Husain, and S. Upadhyaya, "Is rssi a reliable parameter in sensor localization algorithms—An experimental study," in *Proc. Field Failure Data Anal. Workshop*, 2009, pp. 1–5.
- [11] M. Saxena, P. Gupta, and B. N. Jain, "Experimental analysis of RSSI-based location estimation in wireless sensor networks," in *Proc. 3rd Int. Conf. Commun. Syst. Softw. Middleware Workshops*, Jan. 2008, pp. 503–510.
- [12] L. Cheng, C.-D. Wu, and Y.-Z. Zhang, "Indoor robot localization based on wireless sensor networks," *IEEE Trans. Consum. Electron.*, vol. 57, no. 3, pp. 1099–1104, Aug. 2011.
- [13] E.-E.-L. Lau and W.-Y. Chung, "Enhanced RSSI-based real-time user location tracking system for indoor and outdoor environments," in *Proc. Int. Conf. Converg. Inf. Technol.*, Nov. 2007, pp. 1213–1218.
- [14] T. I. Chowdhury *et al.*, "A multi-step approach for RSSI-based distance estimation using smartphones," in *Proc. Int. Conf. New. Syst. Secur. (NSysS)*, Jan. 2015, pp. 153–158.



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