Acoustic Sensor Network-Based Parking Lot Surveillance System

Keewook Na, Yungeun Kim, and Hojung Cha

Department of Computer Science, Yonsei University
Sinchon-dong 134, Seodaemun-gu, Seoul 120-749, Korea
{kwna,ygkim,hjcha}@cs.yonsei.ac.kr

Abstract. Camera-based surveillance systems are commonly installed in many parking lots as a countermeasure for parking lot accidents. Unfortunately these systems cannot effectively prevent accidents in advance but provide evidence of the accidents or crimes. This paper describes the design, implementation, and evaluation of an acoustic-sensor-network-based parking lot surveillance system. The system uses sensor nodes equipped with low-cost microphones to localize acoustic events such as car alarms or car crash sounds. Once the acoustic event is localized, the cameras are adjusted to the estimated location to monitor and record the current situation. We conducted extensive experiments in a parking lot to validate the performance of the system. The experimental results show that the system achieves reasonable accuracy and performance to localize the events in parking lots. The main contribution of our work is to have applied low-cost acoustic sensor network technologies to a real-life situation and solved many of the practical issues found in the design, development, and evaluation of the system.

Keywords: Acoustic source localization, Parking-lot surveillance system, Wireless sensor networks.

1 Introduction

Over the past few years, sensor-network-based parking lot management systems have drawn the attention of researchers. Lee et al. [1] proposed a parking lot application using magnetic and ultrasound sensors to accurately count the number of passing vehicles. Barton et al. [2] and Boda et al. [3] proposed parking lot management systems to find empty parking spaces. Although these systems enhanced the performance of conventional parking lot management systems by using various sensors, most neglected the security issues in parking lots. As the number of large parking lot increases, parking lot crimes such as car theft or vandalism also increase. However, most of the existing parking lot security systems have not efficiently protected these crimes. Parking lot security is generally maintained by car anti-theft systems or surveillance cameras that are pre-installed in a parking lot. These methods, however, have limitations in dealing with emergencies. In the case of camera-based surveillance systems, security guards should monitor the current situation in real time. Due to the practical restriction on constant monitoring of the system, camera-based

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surveillance systems are normally used to provide evidence after accidents have occurred. SensEye [4] was proposed to address this issue. The system approximately detects abnormal movements using sensor nodes equipped with low-performance cameras. Once the movement is detected, a high-performance camera is activated to zoom in on the target. Since there are diverse types of moving objects in a parking lot, detecting abnormal movement is difficult. In the recently proposed SVATS (A Sensor network based Vehicle Anti-Theft System) [5], a small sensor network is constructed in a vehicle to identify unauthorized drivers. Although the system supports quick response and is resilient to attacks, the sensor nodes should be installed in advance. Moreover, the system cannot deal with other types of accidents except for vehicle burglars.

To address the aforementioned problems of the existing systems, we propose an acoustic sensor-network-based parking lot surveillance system. The system uses low-cost microphone-enabled sensor nodes to localize acoustic events such as car alarms or car crash sounds. Once the acoustic event is localized, the system makes use of cameras to pinpoint and monitor the event scene. The contributions of this paper are as follows:

- To the best of our knowledge, the proposed system is the first sensor-network-based parking lot surveillance system using the acoustic source localization algorithm.
- We proposed several mechanisms to improve the performance of the existing acoustic source localization algorithm for real parking lot environments.
- We improved the accuracy of the system by integrating image processing techniques, such as template matching and motion detection, into our sensor network-based system.
- The overall cost of the proposed system is significantly lower than the previous solutions since our system uses a small number of low-cost sensor nodes and cameras.

The rest of the paper is organized as follows. In Section 2, we provide an overview of the proposed system. Section 3 describes the acoustic source localization algorithm and several enhancement techniques. Section 4 presents the integration with surveillance cameras. We present a detailed experimental environment and results in Section 5. We conclude the paper in Section 6.

2 System Overview

Figure 1 illustrates the overall structure of the proposed surveillance system. The system consists of three sub-systems: the Acoustic Source Localization (ASL) system, the surveillance camera system, and the server system. The acoustic source localization system localizes emergency sounds such as anti-theft alarms or car crash sounds. The estimated position of the acoustic event is delivered to the server, which displays the estimated position on the map and sounds an alarm. The surveillance camera immediately adjusts the camera toward the estimated position to capture the event scene, and performs motion detection to find a more accurate position.

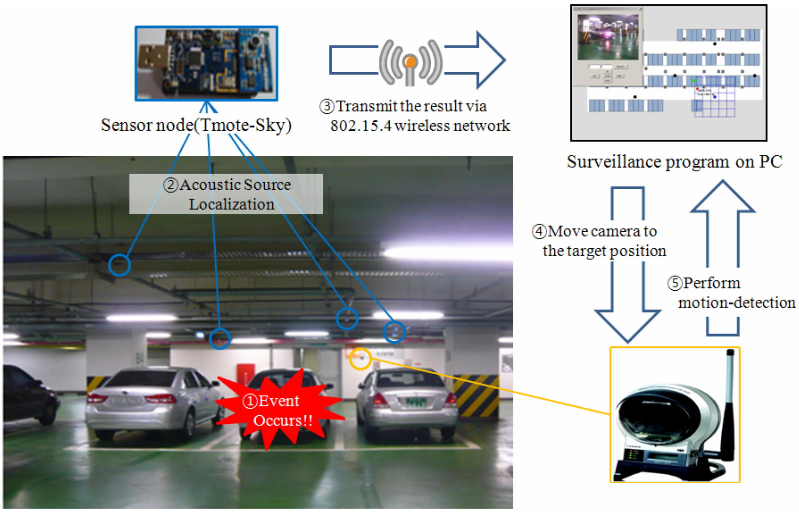


Fig. 1. System overview of the intelligent parking lot surveillance system

Microphone-enabled sensor nodes are attached to the ceiling of the parking lot and sample the current sound level at 3-kHz sampling rates. The Distributed Acoustic Source Localization (DSL) [6, 7] runs on each sensor node to localize the acoustic events. We present the detailed algorithm and enhancements in Section 3. In the surveillance camera system, a set of cameras is installed to cover the entire area of the parking lot. Considering diverse installation environments, we used the cameras that have both wired and wireless network interfaces. The surveillance camera system controls the camera direction to capture the estimated location of the acoustic source. The final location is accurately adjusted with the motion detection algorithm. The surveillance server notifies the supervisor of the event, through the video streamed from the camera system, which monitors the current situation. The server displays the estimated position of the event reported from the ASL system, and then sends the information to the surveillance camera system.

3 Acoustic Source Localization System

In this section, we describe the acoustic source localization algorithm used in our parking lot surveillance system. Several techniques to improve detection accuracy are also described.

3.1 Distributed Acoustic Source Localization

The key part in our system is to find the position of the acoustic source using low-cost sensor nodes. Among the previous techniques, we employed DSL (Distributed acoustic Source Localization), [6, 7] which is the distributed acoustic source localization algorithm. In DSL, sensor nodes exchange their sound detection times when the current sensing value is higher than the threshold. The position of an

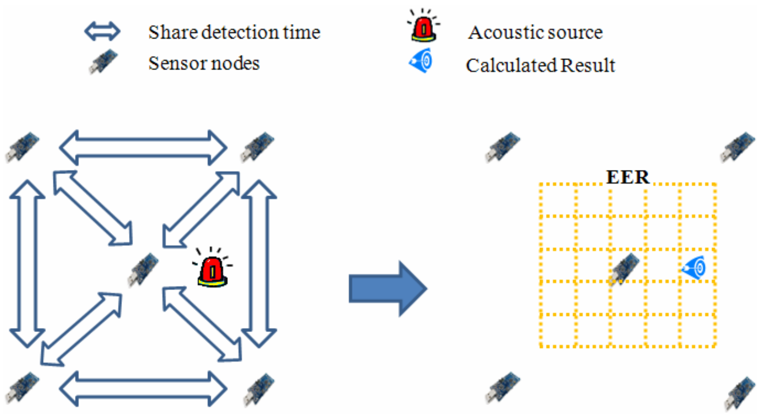


Fig. 2. The DSL algorithm

acoustic source is calculated using order of detection time among sensor nodes. DSL is able to localize sound events irrespective of sound types since the mechanism uses time information. The system requires no additional hardware components except for cheap microphone, in contrast with AOA (Angle Of Arrival) [8] or Beamforming[9].

Previous systems require expensive devices such as additional sampling circuit or high-performance microprocessor to obtain high sampling rates. For example, the shooter localization system [10] used a sensor board with Xilinx XC3S1000 FPGA chip, and the Acoustic ENSBox system [11] used an ARM-based CPU module.

Figure 2 shows the overview of the DSL algorithm [6] used in our parking lot surveillance system. When an acoustic event occurs, sensor nodes share their detection time to elect a leader node that has the earliest event detection time. The leader node calculates the EER (Essential Event Region) [7], which is the possible region of the source location. All nodes check which cell in the EER has a high probability of the acoustic source location by comparing detection times with each other and then transmit the result to the leader node. The leader node finally estimates the source location with the collected data. Detailed descripton on DSL and EER are found in our previous papers [6][7].

Initially, we used the original version of DSL. However, our preliminary experiments conducted at a parking lot did not show as a good performance as we had expected. The problem was revisited, and several error sources were found in the real experiments. The first error source is the low sampling rate of sensor node. The higher the frequency of acoustic events, the higher the errors in detection time. We therefore require an additional algorithm that complements the low sampling rate to accurately detect high-frequency acoustic sources. Second, the location of node deployment affects the localization errors. Since the sensor nodes located on the edge of the parking lot suffer from a lack of information needed to estimate the position of an acoustic source, DSL exhibits worse performance at the corner side than in the middle of the sensor field. The final error source is the duration of the acoustic event. The original DSL algorithm was designed to detect short-duration sound events; hence, one long-duration acoustic event is considered a series of short-duration acoustic events. Repeated detection of one acoustic event may cause energy waste,

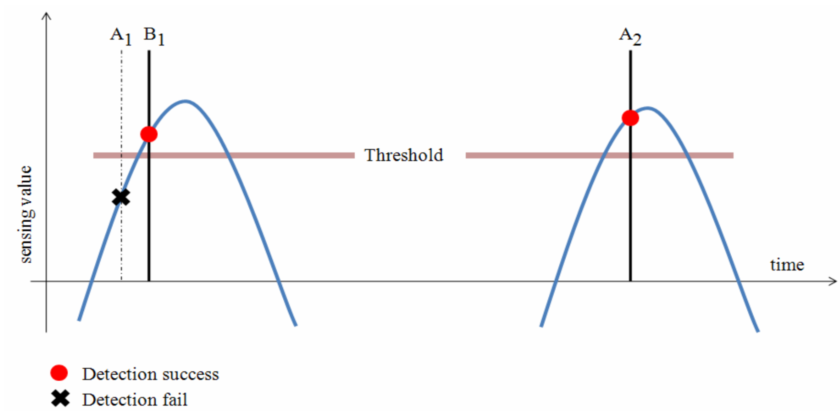


Fig. 3. Sampling time difference between two nodes

and different starting points of the next sensing cycle also cause significant localization errors.

3.2 Improving Accuracy on Detection Time

The low sampling rate of a microphone built into sensor nodes makes it difficult to accurately measure the sound occurrence time. The error rates increase especially in underground parking lots because of the strong echo and many obstacles. To compensate for the errors in detecting time, we propose a compensation algorithm by exploiting log data.

Figure 3 shows the wave form of an acoustic event. At time A_1, node A cannot detect an acoustic event since the sensing value is lower than the threshold. Therefore, node A will detect a sound event at time A_2. However, node B can detect a sound event at time B_1. This means that the phase of the sampling cycle and the threshold level affect the accuracy in detecting the correct time. To address this problem, our compensation algorithm determines the sound detection time using two levels of thresholds. The algorithm has three steps:

1) A buffer with size *n* keeps the measured sensing value in FIFO order.
2) When the current sensing value is higher than the default threshold T_1, the average of the sensing values in the first half of the queue is calculated. The calibrated threshold T_2 is then computed using Equation (1).

$$T2 = avg + \alpha < T1 \tag{1}$$

3) By traversing the second half of the buffer in the time order, the time upon which a sensing value higher than T2 was recorded is determined as the sound detection time.

As shown in Figure 4, the detection time is initially where the sensing value is 2080 with threshold T1. It is then corrected to the time when the sensing value is 1920 with

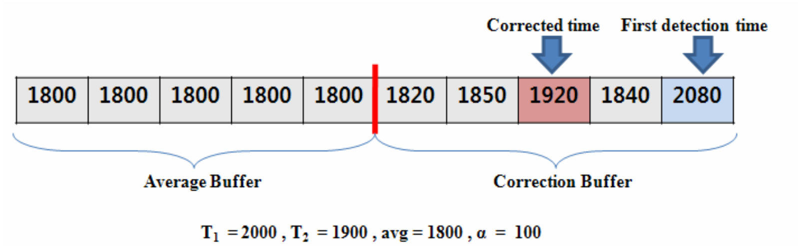


Fig. 4. Correction buffer

threshold T2. Finding the appropriate α value is an important issue. With a low α value, the algorithm is susceptible to surrounding noise. On the other hand, a high α value can cause a problem similar to that of the single threshold T1. In our system, we use the empirically-found α value of 100. With the proposed algorithm, we reduce the error between the detection time and the actual event time since the impact of surrounding noise is alleviated through two levels of thresholds.

3.3 Handling Lengthy Event Source

Repeated detection of one long-duration acoustic event causes energy waste by the sensor nodes. Moreover, different starting points of the next sensing cycle can be an error source. In Figure 5, for example, node 1 and node 2 detected an acoustic event at a similar time. However, different starting points of the next sensing cycle cause jitters, which can be a significant source of estimation errors.

To solve this problem, the proposed system stops sensor nodes from sensing the subsequent acoustic events. Only the node delivering the estimated position to the server continues the sampling to detect the end of the acoustic event. If there is no acoustic event that exceeds the threshold for the predefined time, the acoustic event is assumed to be finished. A message is then transmitted to activate the sampling of other nodes.

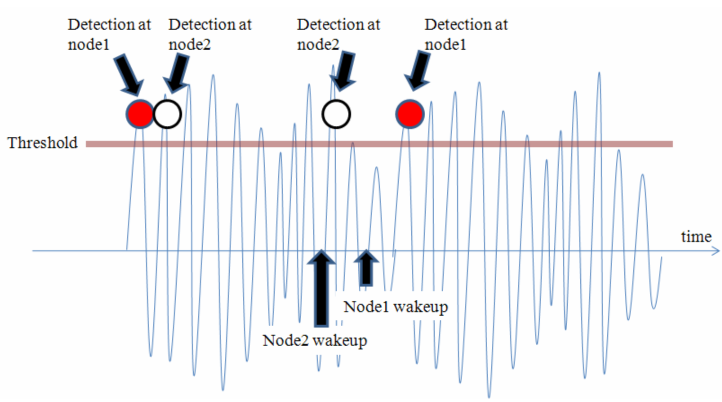


Fig. 5. Detection time error vs. wakeup time

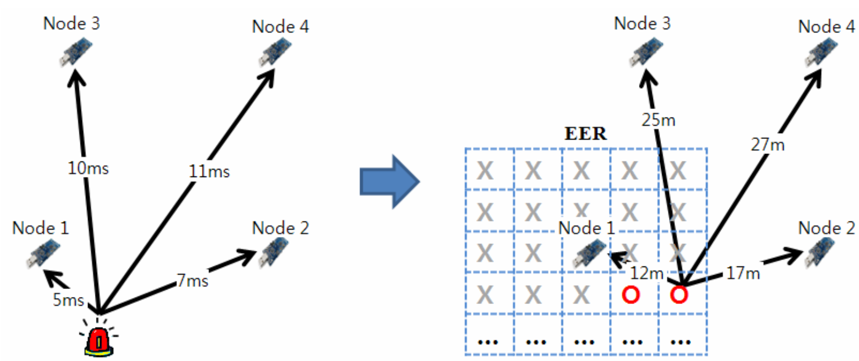
3.4 Improving Detection Accuracy on the Edge

In DSL, the node that has the earliest event detection time is elected as the leader node, and collects event detection times from neighboring nodes. Since the EER is decided based on the gathered information, the distribution direction of the neighboring nodes is important to estimate the position of an acoustic source. The performance of DSL varies depending on the position of an acoustic source. If an acoustic event occurs in the middle of the sensor field, the position is detected with low error. If an acoustic event occurs close to the edge, however, localizing an acoustic source is difficult because of the lack of information required to estimate the position.

To overcome the lack of information on the edge, the proposed algorithm considers the order of the event detection times as well as time differences between nodes. The original DSL uses only time information to determine which node detects the event earlier, whereas our algorithm exploits the differences in event detection times. The algorithm works as follows:

1) Calculate the EER of the leader node using the DSL algorithm and sort the detection times of all the nodes.
2) Divide the EER into discrete units of one parking space.
3) Perform the following procedures at each sub-region.
   (a) Calculate the distance from the current sub-region to each node.
   (b) Sort the distances.
   (c) If the order of the distances does not comply with the order of the event detection times, remove the current sub-region from the EER.
   (d) Finally, remove the current sub-region from the EER if the time difference and the distance difference sequences do not match.
4) Determine the position of an acoustic source by averaging the remaining sub-regions in the EER.

For example, in Figure 6(a), the event is first detected by node 1, followed by nodes 2, 3, and 4. The time differences are 2 ms, 3 ms, and 1 ms, respectively. As shown in Figure 6(b), the current sub-region in the EER satisfies the step 3 condition of the



(a) Acoustic source detection (b) Compare distance with detection time of each cell

Fig. 6. Algorithm on the edge

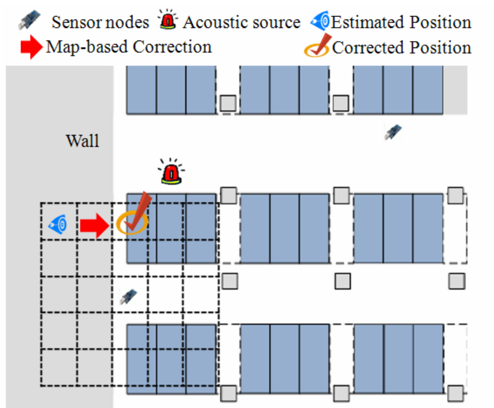


Fig. 7. Map-based localization result

algorithm because the order of the distances coincides with the order of the detection times, and the time and distance difference sequences match.

We conducted experiments to confirm the performance enhancement at the corner side. The average estimation error of our algorithm was 4.3 m, which is 48% of the original DSL. The proposed algorithm reduced approximately 30% of the communication overhead because an additional information exchange is not required after the leader node is elected. In other words, the proposed algorithm reduced the error rates at the corner side and the communication overhead.

3.5 Map-Based Correction

To reduce the location error of a sound event around obstacles, the proposed system exploits map information. The server maintains map information and performs a map-based correction when the estimated position of an acoustic source is received from the sensor nodes. If the estimated position is in the wall or fixed obstacles, the estimated position is discarded or moved. Figure 7 illustrates the correction method. Since the estimated position is in the wall, the method moves the position into the nearest obstacle-free region.

4 Surveillance Camera System

Recognizing the correct situation of a parking lot is difficult in practice if the system depends solely on warnings from the acoustic source localization system. The proposed system uses surveillance cameras to observe the scene and to increase the event detection accuracy. The camera transmits the actual view of the scene in real-time and tracks the scene by communicating with the server. For our system, a camera with wired and wireless communication capability is used for implementation.

Although various correction techniques are used in Section 3 for acoustic source localization, the result with the low-cost microphone sensors still exhibits errors. For instance, in the case of a car collision, the position of an acoustic source and the position of the car may be different because the car can be moved by the force of the impact. The surveillance camera system should therefore cover the scene by considering the error range of the acoustic source localization. If the error range is unreasonably wide, the camera would transmit a picture of a very wide area. In our work, basic image processing techniques are supplemented to find an accurate position.

The first technique is to use the flickering headlights of a car. Typically, when the car alarm is activated, the headlights also flicker. A more accurate position can be found by analyzing the image taken by the camera and by checking if flickering headlights exist. To find the flickering headlights, we used OpenCV [12] library and template matching as in blink detection [13]. The process of finding the position of the flickering headlights is shown in Figure 8. The difference between the current picture and the previous picture from the camera is calculated and then compared with the template image that had been previously acquired. As a result, we determine the position of the headlights with the correlation maxima. According to our experiments, 68% of the maximum correlation value accurately indicates the position of the headlights.

The second technique is to use the motion detection feature that is provided by the surveillance camera. In general, when acoustic source is detected, there is a high possibility of movement being detected around the acoustic source. However, if the motion detection functionality is always active, any kind of normal movement is detected, and consequently, the power consumption increases. In our system, the motion detection feature is activated after the acoustic source is localized and the camera is adjusted to the spot. When the server system detects the acoustic source, the camera spots the detected area and performs motion detection.

The first technique detects the flickering headlights only, whereas the second one detects both flickering headlights and movements of objects. The second technique is used most of the time. However, the first one is exploited if a very accurate position of the car is required.

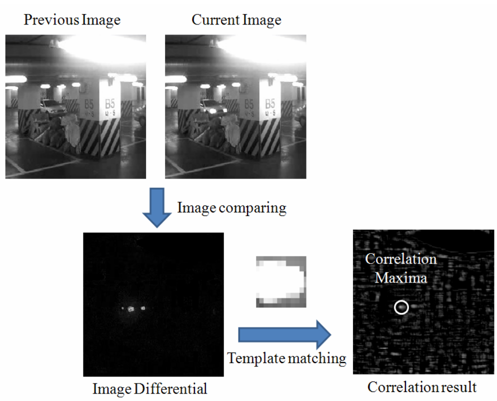


Fig. 8. Detect headlights via template matching

(a) Parking lot (b) Deployed sensor node

Fig. 9. Experiment environment

5 Evaluation

We discuss several experiments that were conducted to evaluate the system. Every experiment was performed in an underground parking lot environment. First, we performed preliminary experiments to find appropriate node spacing for the system deployment. The effect of radio congestion was evaluated, and the localization accuracy of acoustic event was also experimentally obtained. Finally, we conducted experiments to evaluate the overall system with every component activated in a multi-hop environment. In this experiment, the accuracy as well as the reaction time of the system were evaluated.

5.1 Experiment Setup

To evaluate the proposed system in a real environment, we deployed the system in the underground parking lot at our university, as shown in Figure 9 (a). A PC was used for the surveillance server, and we set up the surveillance cameras on the wall. The acoustic source localization system consisted of Tmote Sky [14] with a microphone sensor[15]. RETOS [16] was used for the operating system for the sensor nodes. FTSP[17] and ETA[18] are used for time synchronization in our work. We used ETA as our main time synchronization method since its implementation overhead is smaller than that of FTSP. The sampling rate for the sensor was 3 kHz, and the nodes were installed toward the ground so they could detect sound more accurately, as shown in Figure 9 (b).

5.2 Preliminary Experiments

First of all, to consider the node deployment issue, we performed an experiment that measured the system accuracy according to node spacing. Five nodes were deployed with node spacing varied from 8 m to 25 m. The result is shown in Figure 10. The average error was the biggest when the deployment range was 25 m. This is because the distance between two terminal nodes was 59 m so they could not communicate and obtain all the necessary information.

When the deployment range was shorter than 20 m, the radio communication problem did not occur, and the deployment range of 8 m had the best result. However, as the node spacing becomes narrow, the number of required nodes in the same space increases. In the case of 8-m node spacing, no fewer than 29 nodes are needed to

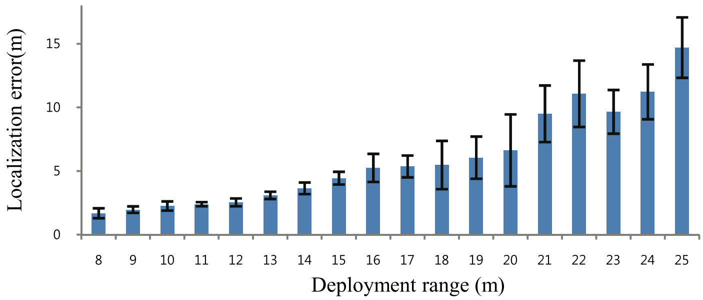


Fig. 10. Localization error vs. node deployment

cover a parking lot size of 88 m by 88 m. Considering both the cost and the accuracy, we decided to deploy 11 nodes in our parking lot size of 88 m by 50 m with spacing of 18.75 m, as shown in Figure 11. All the parking spaces were numbered from 1 to 35 to estimate the accuracy and response time at each parking space.

Second, we conducted experiments to decide the threshold value for the proposed system by measuring microphone levels for various sound events in a parking lot. The measured values from microphone are the ADC(Analog Digital Converter) readings. As Table 1 shows, the values of human dialogue and car moving sounds vary between 1700 and 2300. Consequently we set the threshold with 1600 to 2400 to filter these sounds. In case of slamming car door upon which the sensor node responds, the event can manually be classified with the camera. We plan to classify these sounds automatically using a high performance microphone attached to the camera.

Table 1. Sensing values of various sounds in a parking-lot

	Dialogue	Car moving	Slamming door	Car alarm
Decibel(dB)	65-70	75-85	90-110	105-125
Data from ADC	1780-2050	1715-2291	536-3502	75-3827

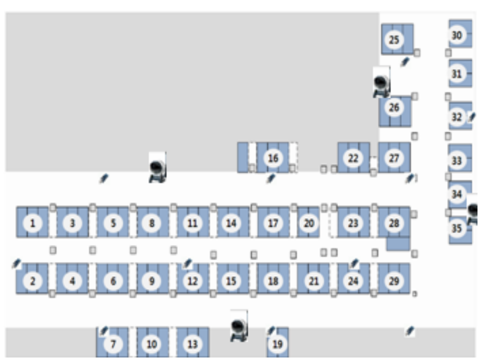
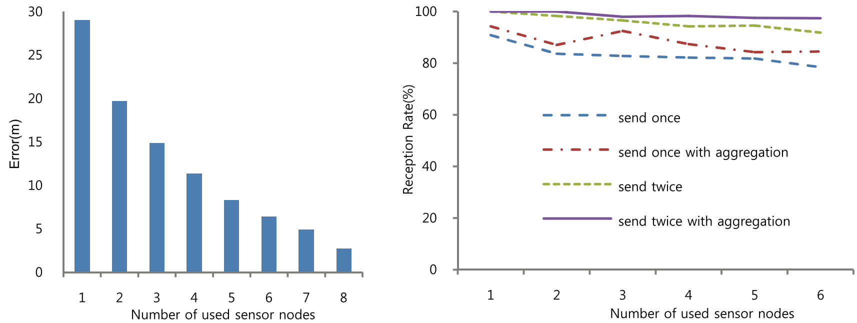


Fig. 11. Map of the parking lot



(a) Localization error (b) Reception rate

Fig. 12. DSL and radio congestion

5.3 Radio Congestion

In the proposed system, sensor nodes broadcast their detection time to the neighbor nodes when they detect an acoustic source. This simultaneous broadcasting can lead to radio congestion, and some nodes may suffer from a lack of the information needed to localize the acoustic source. This causes significant localization errors because the performance of the DSL algorithm strongly depends on the number of nodes that detect the acoustic source. Figure 12(a) shows the localization errors according to the number of nodes in the parking lot. The localization error significantly increases even with two or three nodes dropped out.

Our initial solution was to reduce congestion by having each node broadcast after a certain amount of delay, but this method becomes ineffective as the number of motes increases. The second solution was to use the data aggregation technique. Each mote broadcasts its information two times: first with only its own information, and second with information of other motes together with its own information. As shown in Figure 12(b), sending twice without aggregation is better than once, but the reception rate was still lower than 95% in the case of six nodes. Sending twice with aggregation, however, significantly reduced the congestion, and the reception rate was higher than 95% regardless of the number of nodes.

5.4 Acoustic Source Localization Accuracy

We measured the accuracy of acoustic source localization using 11 sensor nodes in a parking lot size of 88 m by 50 m. The experiment was performed 10 times in each region using a vehicle equipped with an alarm device. Figure 13 shows the localization errors in each parking space. The average error shown in Figure 13 is approximately 4 meters, which is an acceptable result considering the deployment spacing. The error for the outer regions such as Regions 1 and 2 is also as small as that for the central region so we identify that the correction algorithm is working appropriately. In Regions 7 and 35, however, the error was significantly increased because of the wall or pillars near the node.

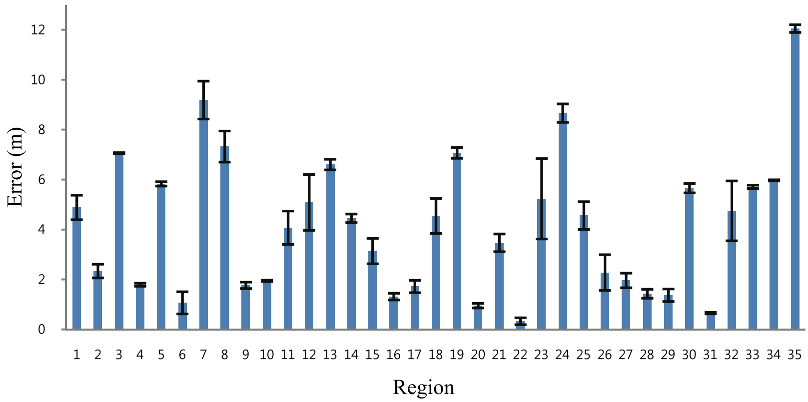


Fig. 13. Acoustic source localization accuracy

5.5 Overall System Accuracy

When an alarm is activated, the position is located using the camera. When the vehicle whose alarm is activated is in the camera picture, we regard it as "successful." Even though the calculated result from the sensor nodes accurately indicates the region in which the alarm occurs, the camera often cannot show the region due to various obstacles or the limitation of the camera angle. To remedy this situation, the cameras were installed symmetrically, and only two cameras that were the closest to the region that the alarm occurs are used to show the result.

With the laptop server, we can see the results moving around various regions. We deployed three router nodes in the experimental environment because the leftmost and rightmost nodes could not directly communicate with each other. Using multi-hop communications, we obtained the result in any region in the experimental environment. The detection result of the region with the alarm using a camera is shown in Figure 14. The car picture in the figure is the actual position of the car, and

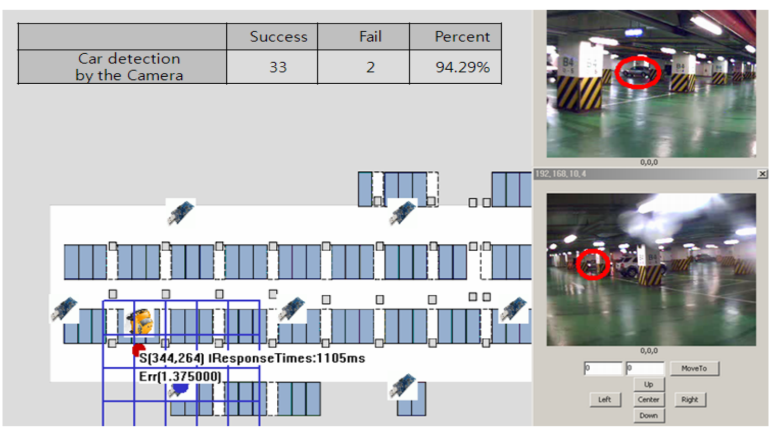


Fig. 14. Car alarm detection

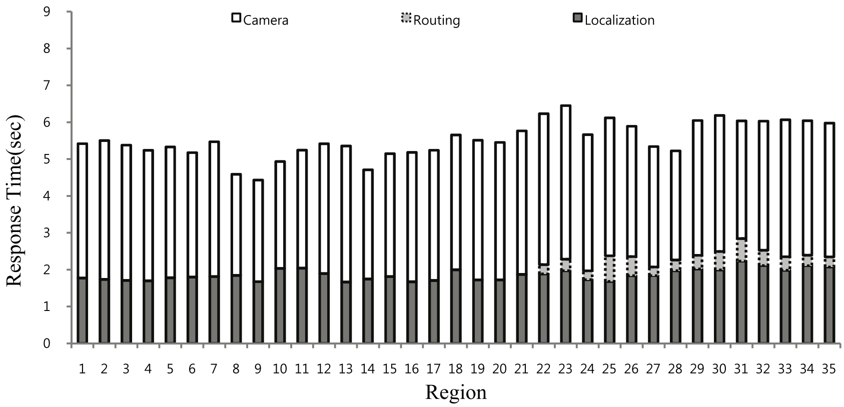


Fig. 15. Response time

the red dot is the estimated position. The success ratio was approximately 94%, which is considered fairly accurate in real environments.

5.6 Response Time

Experiments on reaction time upon events were conducted, and the result is shown in Figure 15. Since the proposed system exchanges time information with the surrounding nodes and the first node that sensed the sound transmits the result, the system imposes a delay in producing the actual result. The reaction time is, therefore, an important metric for the system performance. Figure 15 shows that the output time minimum was 1.67 seconds, the maximum was 2.23 seconds, and the average was 1.8 seconds, excluding the camera reaction time. The response times are influenced by radio congestion. As we discussed in Section 5.3, all nodes send data twice with time slot. With enhanced techniques for handling radio congestion, the response time would be reduced. The server waited for additional results for approximately one second after the reception of the result, because the result can be sent from a node that misunderstood itself as a first node. The camera movement includes motor actuation, which requires 1 to 3 seconds depending on the position of the camera. The overall reaction time including the camera movement was approximately 5 seconds. This mechanical delay is relatively long, but in practical situations this amount of delay is still much faster than a human being manually searches the area upon hearing an event. Additionally, the camera reaction time can be reduced by employing a high-performance camera which has a faster motor speed.

5.6 Discussion

The accuracy of the DSL algorithm strongly depends on the deployment topology of the network. We have in fact deployed the system in various topologies, but the accuracy error was not changed significantly. The reason is that we deployed the sensor nodes with more than 15-m node spacing in the underground parking lot where many reverberation and obstacles exist; hence, the efficiency gain we obtained from node deployment was limited.

As shown in Figure 13, more than 8 m of error occasionally happened in the outer region regardless of the correction algorithm. This is due to the low sampling rate of 3 kHz and the surrounding obstacles, which hinder the accuracy of the detection time. Although this issue can be solved by using powerful sensor nodes with high-frequency sampling, it costs more, and therefore a trade-off between accuracy and cost exists in real system design and deployment.

In our work we did not conduct experiments on power consumption of the proposed system since the system is assumed to be deployed in parking lots where the external power supply is available.

6 Conclusion

In this paper, we proposed a parking lot surveillance system using microphone-enabled sensor nodes. The distributed acoustic source localization algorithm running on sensor nodes localizes the acoustic event in a parking lot. Once the acoustic event is localized, the surveillance camera system moves the camera direction toward the event and performs motion detection to correct the estimated position. The proposed system can localize loud sound events with a small number of sensor nodes and provide the event scene through video streaming in real time. We improved the existing acoustic source localization algorithm with several enhancement techniques, and achieved high accuracy in an underground parking that contained many pillars. The system effectively supervises a large parking lot of 100 vehicles using only a dozen sensor nodes. The experiments conducted in a real parking lot validated the feasibility of the system. Our future work includes further enhancement of the detection accuracy of events, as well as the classification of various acoustic sources.

Acknowledgments

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