A Modified Localization Technique for Pinpointing a Gunshot Event Using Acoustic Signals

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Abstract. This paper proposes a method for localizing a gunshot event using four acoustic sensor nodes mounted at the four corners of a rectangular working area. Each of these nodes involves three sensors to acquire acoustic signals of any gunshot inside the working area. The approach analyzes individual signals received by the nodes to identify sound events using false alarm probability and determine their emission directions exploiting a minimum mean square error estimator and the time difference of arrival of the events. The gunshot location is the quadrilateral center of four crossing points resulting from pairs of adjacent event emission directions. For evaluating the proposed method, a signal including ten real gunshots recorded by a nearby acoustic sensor is delayed and attenuated according to a theoretical wave propagation model to create various signal patterns, which simulates signals received by the installed sensor nodes. Furthermore, the Gaussian noise is added to the simulated signals to emulate the influence of wave propagation environment. This article also implements some mechanisms to compute the time difference of arrival for comparison. They are comprised of the first crossing of threshold and signal, maximum amplitude, Akaike's Information Criterion, and the cross-correlation function. Hence, one of them can be selected for a real application. Experimental results show that the proposed method achieves high accuracy of gunshot localization.

Keywords: Gunshot detection · Gunshot localization · Event detection · Signal detection · Signal processing

1 Introduction

Nowadays firearm violent crime frequently happens. However, relevant people would not be arrested easily if shooting incidents were not located quickly. Therefore, an automatic method of gunshot localization is really helpful in supporting the police to chase and catch criminals immediately.

A firing gun usually emits acoustic muzzle blast waves propagating spherically outwards with a speed of sound in the air [1]. Many papers utilized these signals to

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localize gunshot using sound source localization techniques [2–6]. There are two common localization approaches, which use energy and time difference of arrival (TDOA) [7]. Although the energy-based localization technique can bring about high location accuracy, it is challenging to have a real wave energy propagation model as used in Ref. [7–9]. In contrast, the TDOA-based method is extremely simple because it can localize a sound source without a complex propagation model whose parameters depend on the environment as the energy-based one requires in Ref. [4, 7, 10–13]. Thus, this paper exploits the TDOA-based technique and acoustic signals to localize a gunshot event.

The novel point of the proposed method is that a sound source location is returned by minimizing mean square errors of a known TDOA map and a set of measured TDOA instead of using a direct solution [7, 11–16]. The direct solution is challenging due to complexity of mathematical equations and unavoidable TDOA errors could lead to no solution of those equations. For example, hyperbolic curves [13, 16] do not cross each other at the same point, thus resulting in no gunshot location. As a result, a minimum mean square error (MMSE) estimator is exploited to address the problem in this paper. First, the working area where the firearm situation is monitored is divided into small cells. Depending on acoustic sensor distribution and a specific sound speed in the air, a TDOA map is calculated for all the vertexes of the cells. Next, a MMSE estimator searches all over the cell vertexes for the most appropriate location whose TDOA least differs from measured TDOA resulting from acoustic signals.

Aside from implementing a MMSE estimator, this paper employs a signal detection technique based on false alarm probability [17] for detecting sound events in an acoustic signal. This procedure involves several signal processing stages. The first step estimates the noise level of signal. Next, detection thresholds are computed using the estimated noise level and a given false alarm probability; thus, they can adaptively vary with noise fluctuation. Afterwards, all the adjacent samples that exceed the thresholds are grouped into sound events. The last step eliminates false sound events with the predefined minimum values of amplitude and duration of true events. Hence, TDOA can be directly extracted from true sound events.

Additionally, to choose a suitable approach to the TDOA computation in real applications, the paper compares the effectiveness of various TDOA techniques while evaluating the proposed method.

For evaluating the proposed method, gunshot signals must be available. The next section therefore offers a way to simulate acoustic signals emitted by a gunshot.

2 Signal Simulation

Figure 1 (a) shows a rectangular working area $M_1M_2M_3M_4$ with the size of d x h ($d = h = 500$ m) and a coordinate system Oxy that is established by the rectangle's edges and vertexes. We arrange sensor nodes at the corners of the rectangle to receive signals propagating from any sound source S (x_S, y_S) in the area. A node is comprised of three acoustic sensors M_{ij} ($i = 1, 2, 3, 4$ and $j = 1, 2, 3$) and they are equivalently arranged around a circle with center M_i and a radius of $r = 5$ cm as illustrated in Fig. 1 (b). Hence, the coordinate of sensor M_{ij} is given by:

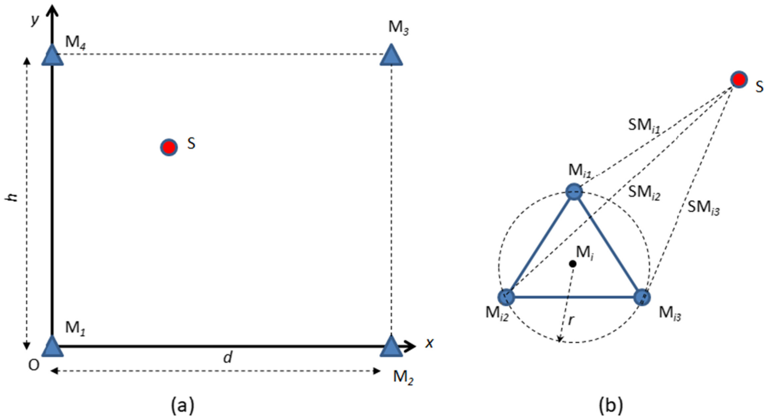

Fig. 1. Sensor arrangement: (a) working area, (b) a sensor node

$$x_{ij} = x_{M_i} - r\sin\left(\frac{2\pi(j-1)}{3}\right), \quad y_{ij} = y_{M_i} + r\cos\left(\frac{2\pi(j-1)}{3}\right) \tag{1}$$

where (x_{Mi}, y_{Mi}) is coordinate of M_i and (x_{ij}, y_{ij}) is coordinate of M_{ij} ($i = 1, 2, 3, 4$ and $j = 1, 2, 3$).

To simulate acoustic signals received by sensors, we exploit a wave propagation model [7, 8] to delay and attenuate a signal loaded from a record of gunshot signals emitted by an AK-47 rifle. As a result, a simulated signal of sensor M_{ij} is given by:

$$z_{ij}(t) = G\frac{z_0(t - t_{ij} + \varepsilon_{ij})}{SM_{ij}^{\alpha}} + n_{ij}, \quad t_{ij} = \frac{SM_{ij}}{C} \tag{2}$$

where t is time, $z_{ij}(t)$ and $z_0(t - t_{ij} + \varepsilon_{ij})$ are simulated and recorded signals respectively, G and α $(1 \le \alpha \le 2)$ are ratios related to a gain of acquisition device and wave attenuation, t_{ij} is flight time of wave from source S to sensor M_{ij}, C is sound speed, ε_{ij} and n_{ij} are added Gaussian noise with means $\mu_\varepsilon = 0$, $\mu_n = 0$ and standard deviations $\sigma_\varepsilon \ge 0$, $\sigma_n \ge 0$, SM_{ij} is the wave propagation distance from source S to sensors M_{ij}, which is calculated as follows:

$$SM_{ij} = \sqrt{(x_S - x_{ij})^2 + (y_S - y_{ij})^2} \tag{3}$$

The two noises ε_{ij} and n_{ij} represent the influence of wave propagation environment such as reflection, diffraction and attenuation on both the arrival time and amplitude of signal, thus making simulated signals become roughly similar to real signals. Figure 2 depicts a gunshot signal source and a simulated signal, in which they are digitized by a sampling frequency of 8 kHz. It can be seen that the simulated signal is lagged behind the signal source, its amplitude and signal-to-noise ratio as well are smaller than the signal source's.

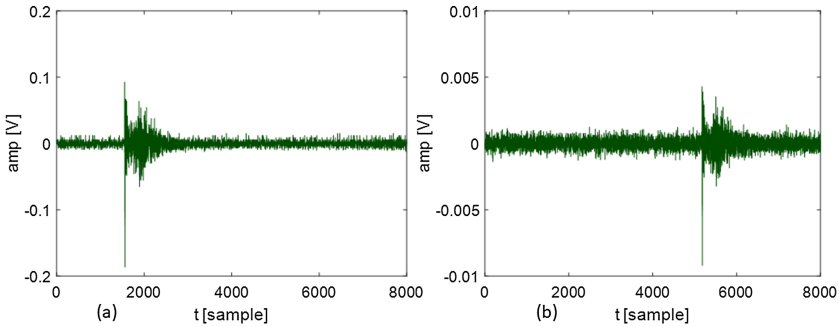

Fig. 2. a) Signal source, (b) simulated signal

3 Methodology

The proposed gunshot localization method comprises two main stages: event detection and source localization as illustrated in Fig. 3.

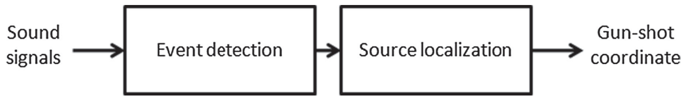

Fig. 3. The overall diagram of gunshot localization

3.1 Event Detection

A gunshot event is defined as a burst in an acoustic signal. To detect it, we exploit a Neyman-Pearson theorem of signal detection probability [17] to calculate a threshold using the following expression:

$$L(z) = \frac{p(z|Hp_1)}{p(z|Hp_0)} > \gamma, \quad p_{FA} = \int_{\{z:L(z)>\gamma\}} p(z|Hp_0) \tag{4}$$

where $L(z)$ is the likelihood ratio, Hp_0 is the signal absence hypothesis, Hp_1 is the signal presence hypothesis, z is an observed set, $p(z)$ is the probability density function, P_{FA} is the false alarm probability, and γ is a threshold. In our application, Hp_0 and Hp_1 are hypotheses of noise and gunshot event respectively and the likelihood ratio $L(z)$ is computed according to the signal amplitude.

Figure 4 illustrates a typical gunshot event with primary characteristic parameters: amplitude, duration, flight time. This event is separated from background noise by a positive threshold (the upper red dash line) or a negative threshold (the lower red dash line). The algorithm of event detection based on Eq. (4) is shown in Fig. 5. The entire process is composed of five phases. The first step estimates the noise background of an input acoustic signal to provide for the second step calculating the positive and negative thresholds. These detection thresholds are adaptive, which vary with the noise level.

The third step compares signal samples with the thresholds. Samples above the positive threshold or below the negative threshold are considered as candidate samples of a gunshot event. Gunshot events are found in the forth step by grouping adjacent candidate samples. Because the detection thresholds are resulting from a false alarm probability, there exist false events. Therefore, the last step (event filtering) is necessary to eliminate false sound events. A true gunshot event must satisfy the following condition:

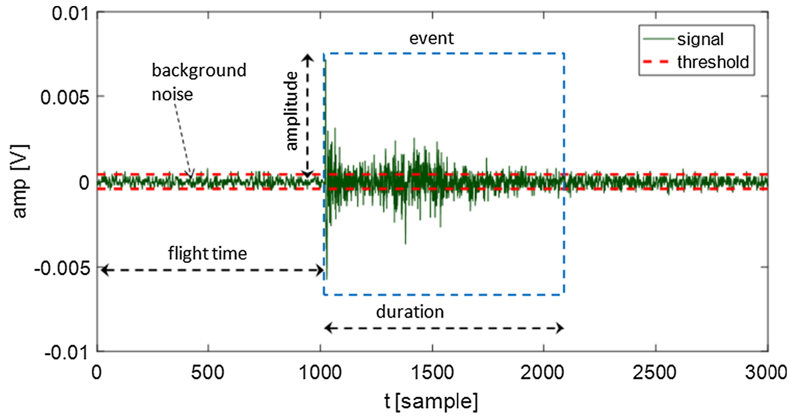

Fig. 4. A typical gunshot event

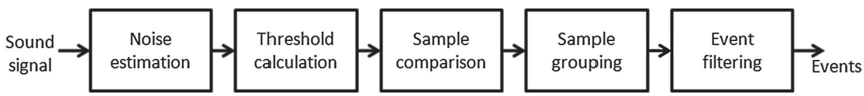

Fig. 5. Gunshot event detection in a sound signal

$$A \geq A_m \wedge N \geq N_m \tag{5}$$

where A and N are the average amplitude and duration of event, respectively, A_m and N_m are their minimum values.

3.2 Source Localization

The working area $M_1M_2M_3M_4$ is divided into cells with the size of $\Delta d \times \Delta h$ as illustrated in Fig. 6. For every vertex H_k (x_k, y_k) of cells, we compute TDOA as follows:

$$\Delta t_{ki} = \frac{\begin{bmatrix} H_kM_{i2} - H_kM_{i1} \\ H_kM_{i3} - H_kM_{i1} \end{bmatrix}}{C}, \quad H_kM_{ij} = \sqrt{\left(x_k - x_{Mij}\right)^2 + \left(y_k - y_{Mij}\right)^2} \tag{6}$$

where Δt_{ki} is an array of TDOA accounted for a vertex H_k and measuring points of a sensor node M_i, H_kM_{ij} is the distance between H_k and M_{ij} ($i = 1, 2, 3, 4$; $j = 1, 2, 3$), C is sound speed.

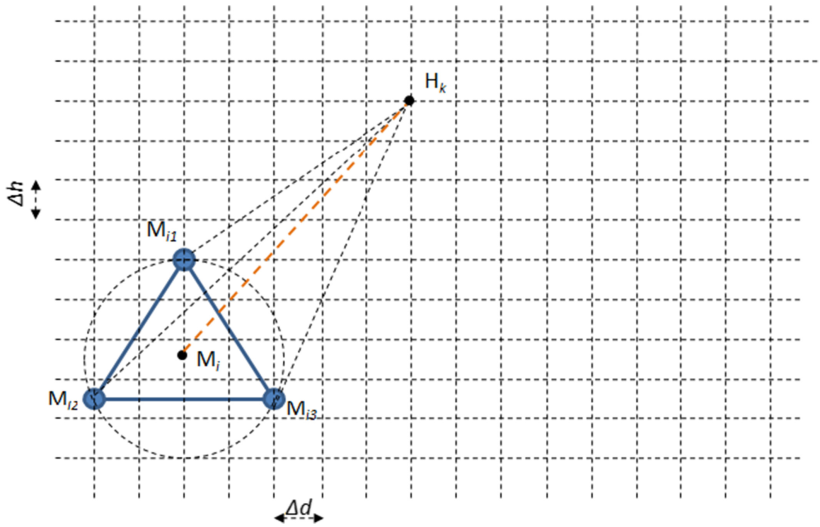

Fig. 6. Determination of gunshot emission direction using a sensor node M_i

It can be seen that TDOA depends on synchronization of signal acquisition between sensor channels. In other words, we hardly synchronize signals of faraway nodes due to complex hardware and software (we need external synchronous devices such as wireless transceivers, Ethernet cables, etc.) while we can simply do this for near sensors without external elements. Accordingly, we consider TDOA between sensors of individual nodes to improve TDOA accuracy as presented by Eq. (6).

Figure 7 shows determining the sound emission direction of a sensor node M_i ($i = 1, 2, 3, 4$). Sound events resulting from sensors M_{ij} ($j = 1, 2, 3$) are conducted to the event grouping. This block picks and groups neighboring events, relying on their arrival time via the following expression:

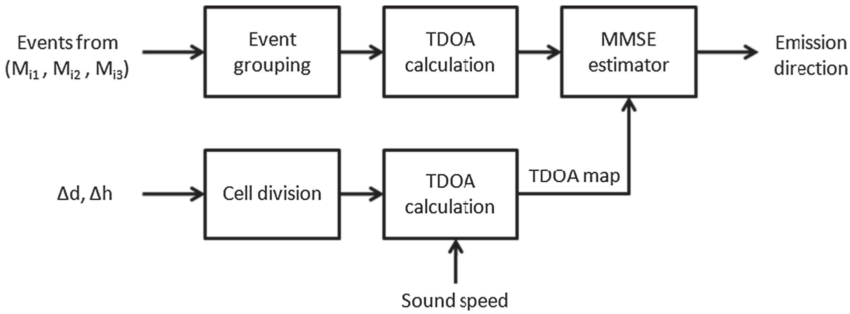

Fig. 7. Determination of sound emission direction

$$|t_2 - t_1| \leq \Delta_m \wedge |t_3 - t_1| \leq \Delta_m, \quad \Delta_m = \frac{M_3M_{12} - M_3M_{11}}{C} \tag{7}$$

where t_j ($j = 1, 2, 3$) is flight time of an event detected in a signal of the j^{th} sensor, Δ_m is a possible maximum TDOA between neighboring events, which is obtained if the gunshot source is assumed to be at the node M_3 and Δ_m is TDOA accounted for sensors of the node M_1. Five event groups from the three sensors M_{1j} ($j = 1, 2, 3$) are indexed as in Fig. 8.

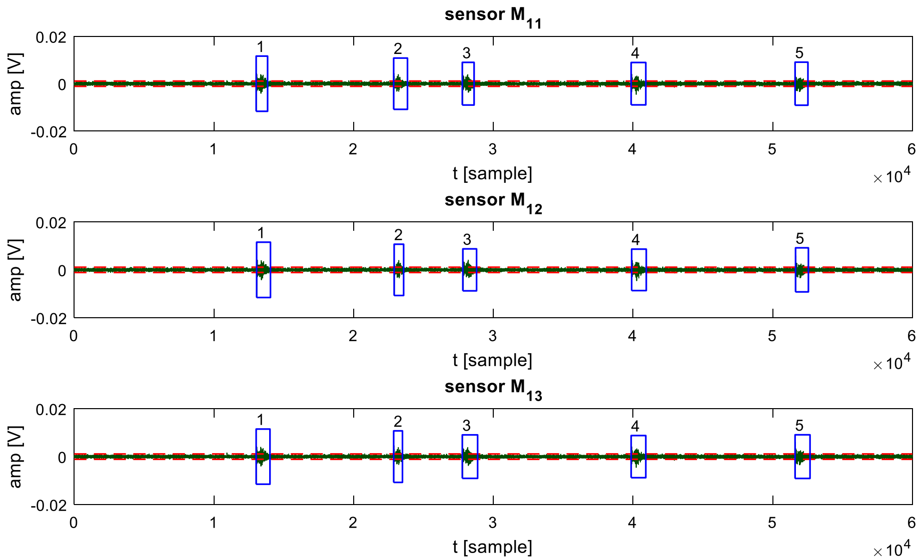

Fig. 8. Grouped events resulting from sensors M_{1j} ($j = 1, 2, 3$)

Based on the TDOA map in terms of cell division and the TDOA of events, we search for a satisfactory vertex H_i (x_i, y_i) against a sensor node M_i ($i = 1, 2, 3,4$) via a MMSE estimator. The MMSE estimator is constructed as follows:

$$H_i \equiv \arg\min_{H_k} MSE, \quad MSE = (\Delta - \Delta t_{ki})(\Delta - \Delta t_{ki})^T, \quad \Delta = \begin{bmatrix} t_2 - t_1 \\ t_3 - t_1 \end{bmatrix} \tag{8}$$

Afterwards, a sound emission direction for a sensor node is given by:

$$v_i = \left(x_i - x_{M_i}, y_i - y_{M_i}\right) \tag{9}$$

where v_i is a direction vector, $i = 1, 2, 3, 4$.

With pairs of vectors (v_1, v_2), (v_2, v_3), (v_3, v_4), and (v_4, v_1), we determine crosses S_1, S_2, S_3, and S_4, respectively. Finally, we achieve a source location S_e which is a quadrilateral center of $S_1S_2S_3S_4$, as illustrated in Fig. 9.

$$x_{S_e} = \frac{1}{4}\sum_{i=1}^{4} x_{S_i}, y_{S_e} = \frac{1}{4}\sum_{i=1}^{4} y_{S_i} \tag{10}$$

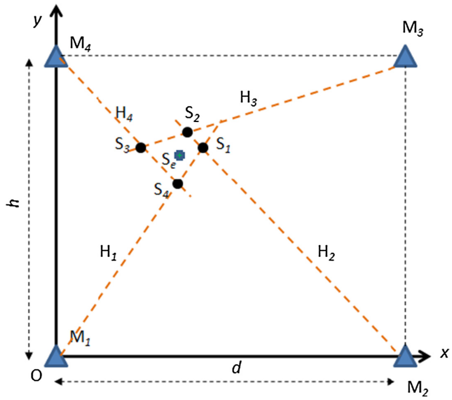

Fig. 9. Gunshot location estimation

4 Experimental Results

To evaluate the proposed method, we initially recorded signals emitted by ten real gunshots using only one nearby sensor as illustrated in Fig. 10. We subsequently simulated signals at sensors M_{ij} ($i = 1, 2, 3, 4; j = 1, 2, 3$) for the four gunshot source locations P_1 (200, 350), P_2 (400, 390), P_3 (340, 150), and P_4 (142, 266) based on Eq. (2) in which $G = 100$, $\alpha = 1$, $C = 340$ m/s (a specific sound speed in the air at 20 °C). We examined two cases: no noise when $\sigma_\varepsilon = 0$, $\sigma_n = 0$ and added noise when $\sigma_\varepsilon = 5$ ms (this results in a statistical location error $\sigma_d = \mathrm{C} \times \sigma_\varepsilon = 1.7$ m), $\sigma_n = 0.3\sigma$ (σ is standard deviation of background noise of the recorded signal). Because the added noises randomly vary with the normal probability density function, we can create diverse signal patterns to trial the proposed method. Besides, we practically chose parameters $A_m = 1.5\sigma$, $N_m = 200$ samples to remove unwanted events using Eq. (5). Finally, the selected cell size is $\Delta d = \Delta h = 2$ m for dividing the working area into cells. Both the simulation and evaluation were implemented in Matlab software.

For a simulation (a gunshot at a location), our approach turned out an estimated location corresponding to a gunshot location as shown in Fig. 11. Additionally, we also implemented four common mechanisms determining TDOA in a trial. The first technique determines the arrival time of signal through the first crossing of threshold and signal (CRS); the second one defines the arrival time of a signal as the position of maximum amplitude (PAK); the third one estimates the arrival time using Akaike's Information Criterion (AIC) [18–21]; the last one directly exploits the cross-correlation function to compute TDOA between two signals (CCR) [4, 22]. Relying on the comparison between their location error averages of the ten gunshots, thus specifying which TDOA determination technique is appropriate for localizing gunshots.

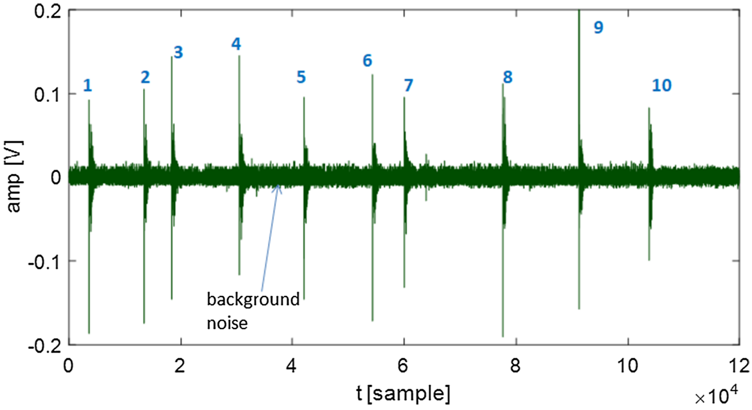

Fig. 10. An acoustic signal containing ten real gunshot events (**1, 2, …, 10**)

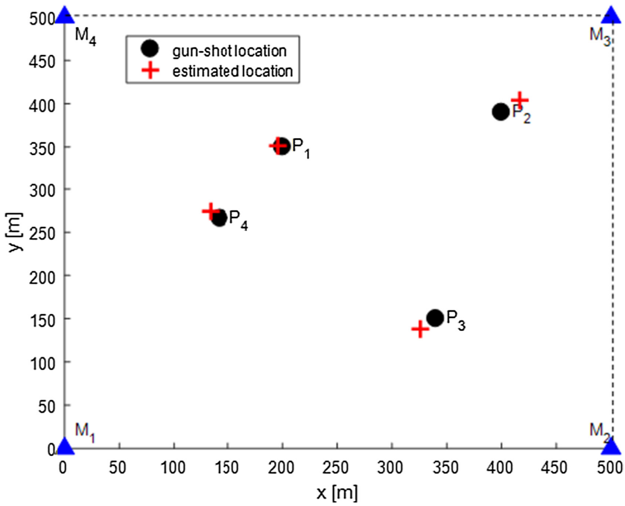

Fig. 11. Gunshots and estimated locations

Tables 1 and 2 show errors of gunshot locations returned by various TDOA techniques in two cases (no noise and added noise). Those are averages of distance difference of the ten gunshots and estimated locations as follows:

$$\delta = \frac{1}{10}\sum_{m=1}^{10}\sqrt{(x_P - x_{em})^2 + (y_P - y_{em})^2} \quad , \quad \delta_r = 100\text{x}\frac{\delta}{\max(d, h)} \tag{11}$$

where (x_P, y_P) is a coordinate of locations P_1, P_2, P_3, and P_4, (x_{em}, y_{em}) is the estimated location coordinate of the m^{th} gunshot ($m = 1, 2, \ldots, 10$), and δ is the average location error, δ_r is a proportion of δ to distance between two sensor nodes.

Table 1. The average location error δ (m) and relative error δ_r (%) using various TDOA techniques without noise

Location	CRS	PAK	AIC	CCR
P_1	1.9 (0.4)	1.0 (0.2)	1.0 (0.2)	1.0 (0.2)
P_2	10.0 (2.0)	9.3 (1.9)	9.3 (1.9)	9.3 (1.9)
P_3	4.9 (1.0)	4.6 (0.9)	4.6 (0.9)	4.6 (0.9)
P_4	13.2 (2.7)	13.6 (2.7)	13.7 (2.7)	13.6 (2.7)
Mean	7.5 (1.5)	7.1 (1.4)	7.2 (1.4)	7.1 (1.4)

Table 2. The average location error δ (m) and relative error δ_r (%) using various TDOA techniques with noise adding

Location	CRS	PAK	AIC	CCR
P_1	68.1 (13.6)	1.0 (0.2)	2.7 (0.5)	1.0 (0.2)
P_2	11.3 (2.3)	9.3 (1.9)	9.1 (1.8)	9.3 (1.9)
P_3	23.3 (4.7)	5.5 (1.1)	6.8 (1.4)	4.6 (0.9)
P_4	31.3 (6.3)	13.6 (2.7)	13.0 (2.6)	13.6 (2.7)
Mean	33.5 (6.7)	7.4 (1.5)	7.9 (1.6)	7.1 (1.4)

It can be seen that if we do not add noise to acoustic signals, all the TDOA techniques turn out similar location accuracy (location error is roughly 7.5 m, corresponding to a relative error of 1.5%). Conversely, their effectiveness is different in the case of noise adding. The CRS method demonstrates the biggest error with an average location error of 33.5 m (relative error 6.7%). This is resulting from the noise presence in acoustic signals. Because the noise fluctuation distorts these signals, the first crossing points of the signals and their detection thresholds are not true arrival times. Although the AIC method (the average location error $\delta = 7.9$ m, relative error $\delta_r = 1.6\%$) improves the location accuracy compared with the CRS method, its error is still bigger than the PAK and CCR methods. The PAK and CCR methods bring about the highest location accuracies in which the CCR method (location error $\delta = 7.1$ m, $\delta_r = 1.4\%$) is slightly better than the PAK one (location error $\delta = 7.4$ m, $\delta_r = 1.5\%$). Obviously, the noise adding does not much influence on the performance of PAK, AIC and CCR methods. In other words, the AIC and CCR methods necessitate more computation than the CRS and PAK ones because they are comprised of extensive computing regarding Akaike's Information Criterion and the cross-correlation function. Hence, we claim that the PAK method is appropriate for localizing gunshots in our evaluation.

5 Conclusions

The paper introduces a modified method localizing a gunshot event based on the time difference of arrival of acoustic signals. Twelve acoustic sensors are arranged in four nodes (each of them comprises three sensors). Sound events are detected in individual signals of nodes through a false alarm probability. Then, the direction of a gunshot event is found with the assistance of a minimum mean square error estimator using the time difference of arrival between acoustic signals acquired by sensors of a node. The sound source location is the center of tetrahedron which is created by four crossing points of four pairs of adjacent emission directions from sensor nodes to the sound event. To evaluate the proposed method, the paper manipulates a signal record of real gunshots to simulate acoustic signals received by sensors relying on a wave propagation model. Furthermore, the article determines the time difference of arrival in various mechanisms to select the best one. The result evaluation for four gunshot locations inside a rectangular working area with size 500 m $\times$ 500 m reveals that the proposed gunshot localization method can turn out high location accuracy and its performance is not much affected by noise (the location errors are 7.1 m (1.4%) and 7.4 m (1.5%) for noise absence and noise adding respectively.)

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