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3D Indoor Localization through a Wireless Acoustic Sensor Networks

Nejah Nasri[1], Mansour Rached[2, 3, *], Samia Chenini[1], and Abdennacer Kachouri[1]

Abstract—GPS is well recognized as the best procedure for outdoor localization. However, it presents limits in indoor localization due to particular geometric difficulties that necessitate specific solution to locate a target inside a building. Also, radio frequency technologies have many disadvantages in indoor localization. Bluetooth and Radio Frequency Identification (RFID) are unsuitable for real-time localization because of latency. Ultra-wideband (UWB) localization needs an expensive hardware. Zigbee presents a high interference with wide range of signal frequency because it operates in unlicensed Industrial, Scientific and Medical ISM bands. Light waves also present some limitations due to interferences from fluorescent light and sunlight. The IR based indoor system has expensive system hardware and maintenance cost. To overcome limits and non-availability of radio waves and light waves, an acoustic solution using an array of microphones is presented as a solution for indoor localization, and an optimized deployment is used to improve precision and restrain error. The aim of this work is to propose a 3D indoor audio localization approach inspired by the principle of functioning of the human ear. In order to achieve our goal, we will use a genetic algorithm to obtain the optimized deployment of the used hardware.

1. INTRODUCTION

Localization is a technique that determines the geographical positions of individuals through their mobile equipment or elements equipped with a specific device [1]. It presents a very interesting field of development and research. In order to determine the position of an object, radio links are often used while analyzing some parameters such as the propagation time, the levels of the received signals and the reception angle. The two essential criteria for characterizing a localization technique are reliability and precision. Precision can be defined through two aspects, which are sensitivity and accuracy measurement.

Thus, the estimation of a precise position seems complicated and inaccessible. The appearance of new networks with wireless sensors is among the solutions to be examined to ensure localization inside buildings. To perform this localization, there are two different approaches which can be applied, either the sensor looks at its environment and realizes its positioning by itself, or it does not locate itself immediately, and the localization is accomplished by the other nodes of the network. In order to explore the notion of indoor localization, several techniques and positioning systems are achieved. The primary methods are based on radio signals (Bluetooth, RFID, UWB, Wi-Fi, etc.), infra-red signals (WIPS, Active Badge, etc.), visible light (LED, etc.), onboard sensors (barometers, MEMS, etc.), and acoustic signals (ActiveBat, Cricket, etc.) [2].

In many cases, radio-frequency remains insufficient to give the exact coordinates of an indoor object because of interference and obstacles [3]. Technologies using radio signal like WIFI, Bluetooth, UWB and RFID based fail to achieve sub-meter accuracy [4]. These technologies present many advantages

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* Corresponding author: Mansour Rached (m.rached@seu.edu.sa).
[1] National Engineering School of Sfax, Street sokra 4 km, 3038 sfax, Tunisia. [2] College of Computation and Informatics, Saudi Electronic University, Tabuk, Saudi Arabia. [3] Université de Tunis El Manar, F.S.T., LIP2-LR99ES18, 2092 Tunis, Tunisia.

in indoor localization but require a wide-ranging setup and fine-tuning. Also, localization based on IR report localization error for the fixed target is designed mainly for moving objects [5]. In order to attain sub-meter accuracy and overcome the unavailability and drawbacks of radio or IR technologies, audio signal based localization systems have to be proposed.

Table 1 shows characteristics of several technologies used in indoor localization.

Table 1. Comparison of technologies used for localization.

	Accuracy	Power consumption	Coverage	Cost
WiFi [18]	5 cm	High	Outdoor/ Indoor	Low
RFID [19]	14 cm–2 m	Low	Indoor	Low
Bluetooth [20]	95 cm average	Low	Indoor	High
ZigBee [21]	3 m–5 m	Low	Indoor	Low
Ultrasound [22]	3 cm–30 cm	Low	Indoor	Medium
IR [23]	2 cm–50 cm	Low	Indoor	High
UWB [24]	20 cm–30 cm	Low	Indoor	High

IR signals have some disadvantages, such as interference and expensive materials. Radio frequency technologies (RFID, Bluetooth (RSSI), WLAN) present precision of several meters, and wideband based technologies (UWB) are costly for wide-scale use.

The proliferation of acoustic processing signal provides a promising future for serving human (or object) localization in indoor scenario. Acoustic source localization consists in determining position of an acoustic source with respect to a known coordinate system. However, acoustic based systems will enable a large number of innovative applications (civil, military, etc.) because of interest accuracy levels and low complexity. The choice of acoustic signal for localization comes with its several returns. Acoustic signal is usually unaffected by changes in the store layout or human presence unlike magnetic fields and Wi-Fi signal strength. However, depending on the frequency and amplitude, acoustic signal can be well detected by microphones.

The proposed localization approach consists in introducing a wireless audio network based on microphones that allow to determine a 3D localization. Audio localization is the positioning of a person or object using the principal of human hearing. It is also used to locate a moving mobile (4D localization). Before their implementation, microphone networks deployment requires a phase of simulation to ensure proper functioning. Therefore, experimental evaluation is realized to guarantee the technical design and to validate theatrical results.

In the studied literature, we can deduce that Genetic Algorithm represents a good result to obtain the optimal solution for 3D indoor localization. The authors in [6] develop a Genetic Algorithm in order to obtain the optimized deployment of sensors in a particular context. The studied space in their paper is divided in parts and priorities area fixed for each part. The integrated priorities make the deployment problem feasible in the case of region with different important levels. Kassarwani et al. [7] used a Genetic Algorithm to calculate the optimized value of the gains of proportional and integral (PI) controllers. They used MATLAB software to implement their program. In the context of wireless sensor network, the problem of energy consumption of sensors by radio communication is critical. The authors in [8] use the Genetic-Algorithm-Based Energy-Efficient Clustering (GAEEC). The authors also compare the proposed algorithm with the Low-Energy Adaptive Clustering Hierarchy (LEACH). The simulation results show that GAEEC is better than LEACH on three levels, namely, a longer stable region, improved throughput and in the energy conservation.

The authors in [25] introduce a mathematic model of sensor deployment and location based on signal power, which decays as distance from the target increases. Subsequently, a generalized Likelihood Ratio Test (GLRT) based decision fusion method is proposed to detect target presence/absence in WSN field. This work presents the performance of fusion of Maximum Likelihood (ML) and Cramer-Rao Lower Bound (CRLB) in terms of detecting an unknown source with known location (i), detecting an unidentified source with known observation coefficient (ii), and (iii) fusion conditionally dependent decisions, respectively.

In [26], authors focus on decentralized detection of non-cooperative target transmitting an unknown deterministic signal at unknown position. In this research, the scholars came up with a generalized version of Rao test characterized by a low complexity compared to GLRT. In addition, the authors developed a reasonable criterion for optimized Rao in terms of system false and detection probabilities. Simulation result in [26] shows that G-Rao presents only marginal loss over the GRLT for the detection of target over Region on Interest (RoI).

The authors in [27] study a decentralized detection of a non-cooperative source characterized by a fluctuating signal. To overcome problem of Gaussian Noise and attenuation signal a Generalized Locally Optimum Detection (G-LOD) based on Davies' framework is investigated, and a novel sensor threshold optimization is developed. From this research, we deduct that G-LOD is characterized by lower complexity than Generalized Likelihood-Ratio Test (GLRT). Furthermore, simulation result in this study illustrates that G-LOD presents better performance than GLRT in terms of detection and moderate loss compared to position clairvoyant (PC) LOD.

In [28], the authors discuss the same problem presented in [25, 26], and [27] and simultaneously focus on the complexity issues. [28] introduces a method of detection based on several fusion rules based on (GLRT), Bayesian approach, and hybrid combination between the two. From the results presented in this paper, we deduct that all rules have similar performance in terms of detection. To reduce computational complexity, the authors propose two sub-optimal fusions with respect to previous rules. In [28], error-prone channels are also considered for target detection.

The paper is organized as follows. In Section 2, we present a survey of indoor localization theory, techniques of target detection, and classification of localization methods. In Section 3, we introduce our 3D localization approach, the setup of experiment and specify the conditions under which the measurements were performed and the equipment used. Section 4 presents a 3D deployment based on genetic algorithm, and we discuss the measurement results, leading to the conclusions presented in Section 5.

To determine audio source localization, different decision parameters should be considered and summarized in Table 2.

Table 2. Notation and basic description of employed symbols.

Symbols	Basic definition
D	Distance between two microphones
d	Distance between receiver and transmitter
v	is the propagation speed of the signal
θ	Angle of received signal
$C_{s_1 s_2}(t)$	The inter-correlation function is used to estimate the delay between two signals $s1(t)$ and $s2(t)$
$ni(t)$	Noise affecting signal propagation

2. AUDIO SOURCE LOCALIZATION

Audio localization is the ability to determine the geographic position of a sound source. This specialization constructs the subjective sound spaces with identifying the direction of the sound sources. Its azimuth power and distance refer the direction of the sound from the source. With the presence of sound sources in a three-dimensional spherical acoustic field, the listener can locate the position of each source by the binaural character of its auditory system. The auditory system is based on the following acoustic indices [9]:

- Spectral information.
- Interaural time differences (ITD).
- Interaural phase differences (IPD).

- Interaural level differences (ILD).

2.1. Indoor Localization Process

For majority of applications, specifying the origin of the detected events includes determining values which detail the parameters characterizing this event, such as the determination of the geographical position.

A coordinate system is defined in the first phase to determine the location of the target object. The second phase consists in estimating distances. Finally, a localization Genetic Algorithm will be applied.

- The definition of a coordinate reference: It is to set a relative or absolute coordinate system in which we will determine the position of the sources. This knowledge presents an intermediary between the real and virtual coordinate systems.
- Estimation of distances: This task is critical; it depends mainly on the communication equipment. Indeed, by collecting indicators of the signal, we can estimate the distances separating the receivers and transmitters.
- Localization consists in giving geographic optimized coordinates to each node. In the network only anchors nodes have a known and fixed coordinate.

Localization algorithms use the flow of information given by each node to determine the positions of all sensors. To develop localization algorithms, it is necessary to take into account some factors like reducing the computational complexity and flexibility to the number of nodes in the network. A localization algorithm aims to achieve some design objectives such as:

✓ Reduce the energy consumed in the process of localization.

✓ Tolerance to possible faults such as power unavailability, malfunction of some sensors and signal scrambling.

✓ Preservation of the performance of the algorithm even in the case of scaling up.

2.2. Classification of Localization Methods

Broadly, localization methods can be classified according to the distribution of calculation process (centralized or distributed):

- Centralized methods:

The centralized localization method is principally based on the collection of information (distances, signal, neighbors, etc.) by the sensors from their environment, and then the transmission of these data to the fusion center that collects them from sensors and forms a global situational evaluation. Based on these evaluations, fusion center will make a decision.

The process of this localization is carried out by a powerful central machine regarding computing performance, processing and energy resources [10]. This unit estimates distances and determines positions. One of the most significant disadvantages of this algorithm is time-calculation that grows with the size of the network due to data collection and the huge number of transmitted messages; therefore, the localization process time is significant.

- Distributed methods:

In this method of localization, all nodes communicate together to determine the distances and exchange information about the neighborhood (estimated angle, distance) to derive their positions in a distributed manner. Each sensor must know its position and determine locations of the sources, without the contribution of any central unit that would perform the calculations. Thus, the distributed algorithms ensure the direct localization of the sources in the coordinate system established by sensor positions. These algorithms are not complicated which makes the distributed method useful in the case of large-scale networks because it avoids high consumption of energy resources and in time processing [11].

The distributed localization method can be classified into three categories:

✓ Anchor-based algorithm: We use the distance information between nodes to determine the location of static nodes.

✓ Distributed relaxation-based algorithm: Followed by the refinement step, typically in which each node adjusts its position to approximate the optimal solution.

✓ Distributed algorithm based on a coordinate system: In this case, the sensor network is divided into sub-regions (clusters) of small sizes. Each of these regions is responsible for creating an optimal local map, and then these maps will be merged into a single map.

The localization techniques differ with regard to the hardware capabilities of devices (Range-based methods). Range-based methods use a range of measurements. Indeed, this method exploits information on angles or distances to determine the locations of the sensors. These data can be obtained using metrics such as TOA (Time of Arrival), AOA (Angle of Arrival), TDOA (Time Difference of Arrival) and RSSI (Received Signal Strength Indicator) [12] and [13]. Range-based methods are characterized by a fine resolution. In fact, they involve two basic steps. The first one is a distance estimation step, and the second consists in deriving data of unknown positions obtained during the first step.

2.3. Channel Parameters Localization

Channel parameters are vital for localization applications. In this section, we describe the different channel parameters that allow us to determine the distances and the direction necessary to obtain the position of the detected event. Examples of these parameters include: RSSI, TOA, TDOA and AOA.

- RSSI:

RSSI is a measurement of the power present in a received radio signal. The power of reception and transmission of a signal can be exploited to determine the distance between two sensors. Using RSSI, we can determine the losses due to the propagation of radio waves, and then we can translate these losses into distance using empirical models. This method is not a good solution in terms of performance, as it is sensitive to noise and interference. The main advantage of the RSSI is its low cost.

- TOA:

This technique assumes that all sensors in the network are widely synchronized. The TOA method is based on precise and accurate measurements of time between transmission of the wireless signal and its arrival to another location. Therefore, the clocks of the sensors must be strictly synchronized in order to have precise indices. As a result, when a signal is emitted by a source at instant t_1 and if it is received at time t_2 by the sensors, the distance separating them can be expressed as follows [14]:

$$D = v(t_2 - t_1) \tag{1}$$

with D is the estimated distance between the source and the receiver, and v is the propagation speed of the signal. The TOA technique requires the use of very precise equipment. Speed depends on a few factors related to the environment.

The inter-correlation between the transmitted and the received signal from sensors determines the propagation time. $R_i(t)$ is the signal received by the sensor i and $S(t)$ the transmitted signal with t_i delay and $n_i(t)$ noise:

$$R_i(t) = S(t - t_i) + n_i(t) \tag{2}$$

The inter-correlation function between the transmitted and received signal during period T_t is obtained by the integration between the products of these signals [15]:

$$R_{S,R_i}(\tau) = \frac{1}{T_t} \int_0^1 s(t) \times R_i(\tau) dt \tag{3}$$

- TDOA:

The TDOA technique not only is based on the radio signal, but also requires other hardwares such as microphone and loudspeaker. Some systems use audible frequencies while others use ultrasound. The TDOA method is similar to the TOA technique since it also uses the signal propagation time. It is based on the difference in the arrival times of two signals. In addition, the TDOA technique ensures very high positional accuracy. Many algorithms use it because it is more accurate than other methods.

As shown in Figure 1 we have three sensors denoted by 1, 2 and 3, between each pair of sensors; the difference of arrival time is calculated as follows:

$$t_{i,j} = t_i - t_j \quad \text{for} \quad i \neq j \quad \text{with} \quad i, j \in \{1, 2, 3\} \tag{4}$$

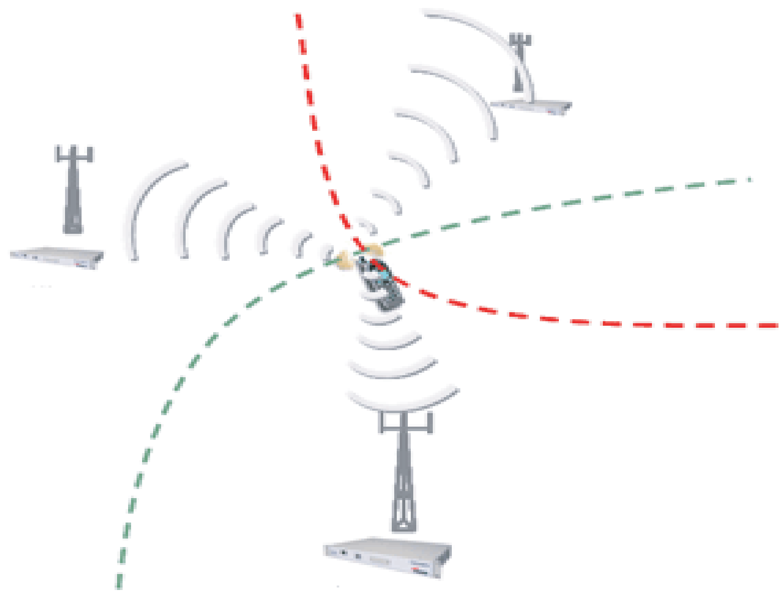

Figure 1. Localization by TDOA.

The difference in distance between the sound source and each pair of sensors i and j is given by:

$$v \times t_{i,j} = \sqrt{(x_i - c_x)^2 + (y_i - c_y)^2 + (z_i - c_z)^2} - \sqrt{(x_j - c_x)^2 + (y_j - c_y)^2 + (z_j - c_z)^2} \tag{5}$$

with v is the propagation speed of the signal, (c_x, c_y, c_z) the source position, and (x_i, y_i, z_i) are the positions of the anchors. The correlation method is a conventional method for the estimation of TDOA. The estimated TDOA can be determined using the inter-correlation between the signals picked up at a pair of sensors.

Consider that signal $R_i(t)$ is the signal detected by sensor i and that $R_j(t)$ is the signal detected by the sensor j. The two signals are written as follows:

$$\begin{aligned} R_i(t) &= S(t - t_i) + n_i(t) \\ R_j(t) &= S(t - t_j) + n_j(t) \end{aligned} \tag{6}$$

with t_i and t_j representing the delays respectively at sensor i and sensor j, and $S(t)$ is the signal emitted by a source. $n_i(t)$ is the noise.

The inter-correlation function of the signals received by the two sensors is expressed by [15]:

$$R_{R_i,R_j}(\tau) = \frac{1}{T_t} \int_0^1 R_i(t) \times R_j(t - \tau) dt \tag{7}$$

- AOA:

This method defines the angle of incidence of an incident signal at the receiving sensor. The AOA technique provides more accurate results than that of localization based on the RSSI. There is no necessity of synchronization between sensors in AOA approach.

3. 3D ACOUSTIC LOCALIZATION APPROACH THROUGH AN AUDIO NETWORK

Localization in WSNs has been typically realized by measuring the received signal strength (RSS) or time of arrival (TOA) of radio signals.

However, the RSS approach, while being significantly inexpensive, sustains important errors due to channel fading, long distances, and multipath. In the context of acoustic signal processing, the network of wireless audio sensors also provides advantages with respect to wireless sensor networks. For example, they enable an increased optimized deployment and coverage by distributing microphone nodes over a larger volume, a scalable structure, and possibly better signal-to-noise ratio (SNR) properties. In fact, since the ranging precision depends on both the signal propagation speed and the precision of the TOA measurement, audio signals may be favorite with respect to radio signals [16].

Our approach presents an audio localization system, which makes us able to estimate the 3D indoor localization of an object. The description of the localization mechanisms will be restricted to the case of a single source present in the closed field as well as the problems associated with the design of such a system.

Figure 2 describes a step-level of 3D indoor localization system.

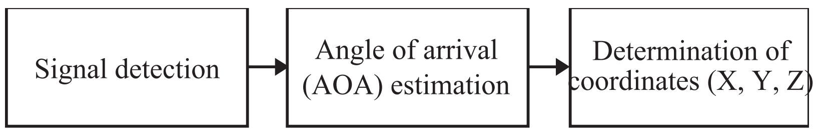

Figure 2. Process of 3D audio localization.

In our system, we use three microphones along each axis in order to obtain more information for the localization of the source.

All the recordings are made in a laboratory computer in the faculty of sciences of Gafsa-Tunisia with a normal background noise and whose reverberation time is large enough to be able to detect the vibration sufficiently. The microphones used for experiments have an integrated FET transistor placed in a plastic support; three holes have been drilled for fixing the microphones. It is necessary to know minimal information about the directivity of the microphones and their position. The experiment requires the installation of a 60 cm bar. Two microphones are placed on the right and left sides, and the third is placed in the middle, which means that the distance between each pair of microphones is 30 cm.

3.1. Estimation of Direction of Arrival

Our experiments are mainly based on TDOA. After processing signals based on the computational algorithm, we determine the angle of the received signal by the following mathematical formula [17]:

$$\cos(\theta) = \frac{d}{D} \tag{8}$$

with $d = v \times \tau$ and D designates the distance between the two microphones.

So, the previous equation becomes:

$$\cos(\theta) = \frac{v \times \tau}{D} \tag{9}$$

Then angle θ is determined as follows:

$$\theta = \cos^{-1}(\frac{v \times \tau}{D}) \tag{10}$$

The intercorrelation function is used to estimate the delay between two signals $s_1(t)$ and $s_2(t)$:

$$C_{s_1 s_2}(t) = \int_{-T}^{+T} s_1(t) s_2(t - \tau) d\tau \tag{11}$$

3.2. Proposed Approach for 3D Localization

Typically, our approach assumes that there are source-emitting sounds and a collection of fixed microphone anchor nodes placed in known positions. When the sound source transmits a signal, the different microphone nodes will estimate the time of arrival (TDOA). The proposed system is equipped with nine anchors sensors outfitted with nine microphones. The TDOA refers to the difference of propagation time from the source location to pairs of loudspeakers. Figure 3 illustrates the general principle of 3D audio localization of a sound wave detected by a network of microphones.

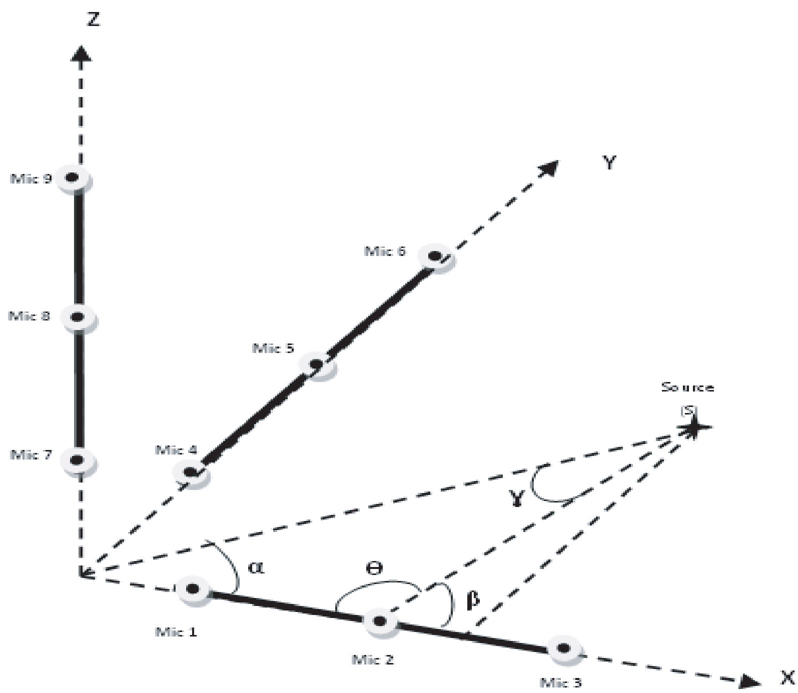

Figure 3. Conceptual deployment of microphones for self-localization scenario.

Our process of audio localization begins with signal acquisition. The microphones demodulate the received signal using the appropriate frequency. We calculate the inter-correlation between the signals picked up by the microphones to determine the maximum of the correlation. Once the temporal position of the maximum of the inter-correlation is established, it is possible to deduce delay between these signals. At this level, we estimate the angles of arrival, and we can determine the 3D coordinates by applying the trigonometric formulas. The following mathematical equations explain how to assess x:

$$\frac{BS}{\sin\alpha} = \frac{AB}{\sin\gamma} = \frac{AS}{\sin\theta} \tag{12}$$

$$\begin{aligned}
BX &= BS\cos\beta \\
BS &= AB\frac{\sin\alpha}{\sin\gamma} \quad or\ \gamma = 180-\alpha-(180-\beta) \\
BS &= AB\frac{\sin\alpha}{\sin(\beta-\alpha)} \qquad (13) \\
\rightarrow BX &= AB\frac{\sin\alpha}{\sin(\beta-\alpha)}\cos\beta
\end{aligned}$$

The angle α is determined by calculating the delay between mic1 and mic2. The angle β is determined by the calculation of the delay between mic2 and mic3. Based on these trigonometric equations, the coordinates (x, y, z) can be determined by symmetry.

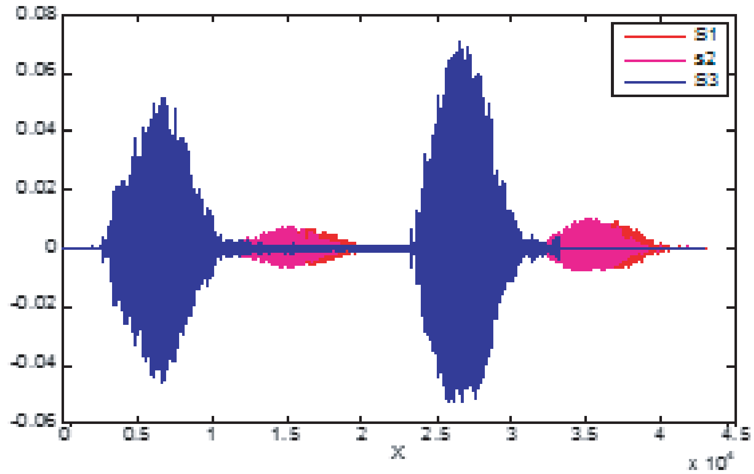

Figure 4. Delayed signals.

Figure 4 presents the three signals received by the different microphones (mic1, mic2 and mic3).

The received signals do not resemble each other. Therefore, a significant difference between the time of arrival of the direct sound and the reflected sound is perceived by the system. These delay times are integrated to estimates angles of arrival.

We are trying to track in real time a source moving in the laboratory room to determine the direction of the sound source as shown in Figure 5.

We have implemented and deployed the audio network localization system in laboratory computer. The test datasets are each obtained from real deployment that replays the exact scenario.

3D acoustic localization refers to the acoustical engineering technology used to estimate sound source angle and distance. We investigate the performance of our proposed system in real environment.

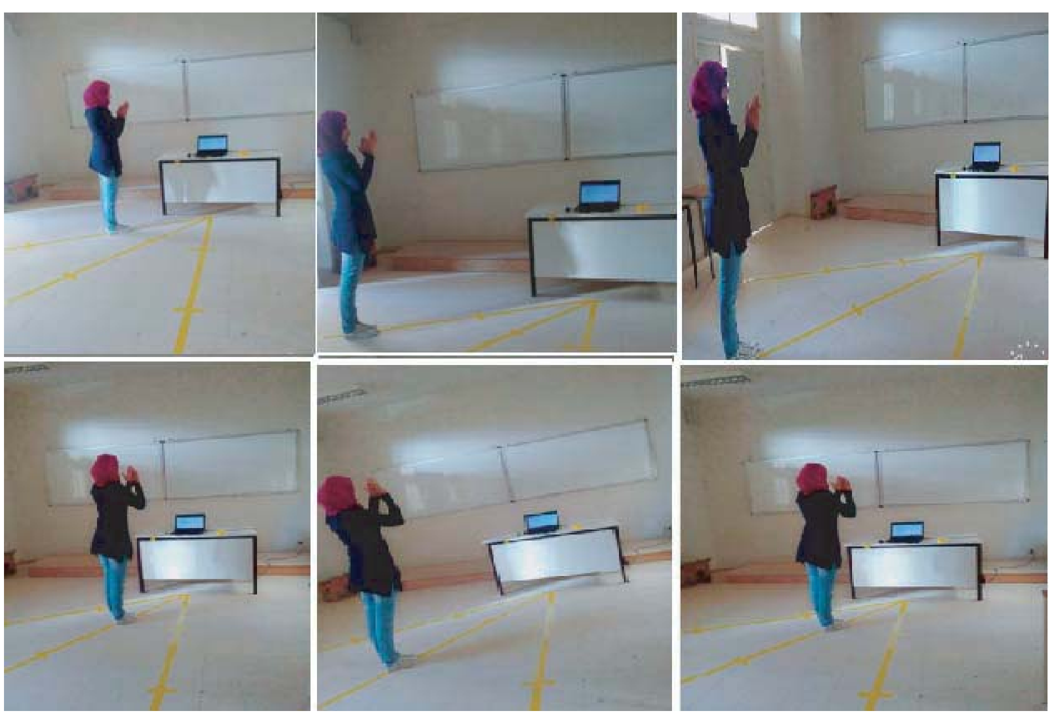

Figure 5. Real-time testing.

Table 3. Experimental parameters.

parameters	value
Number of microphones	9
Sampling frequency	32 kHz
Sound source distance	0–3 m
Distance between Mic	30 cm
Frame size	2048 samples
Overlapping time	50%
Overlapping frequency	50%
Noise type	Additive White Gaussian Noise

We use 9 microphones (Electret Condenser Microphone). For specific setup Table 3 details real data used for experimental prototyping.

During development, we use a clapping of hands for testing a new skill of our system, and the maximal detection range of audio sensors is 3 meters.

Sound directional angle detected is presented in Table 4 to evaluate the accuracy of our system with the real angle. We fix angles to: 45°, 90° and 120° and change the distance (DS) between source and microphones. Table 4 presents a comparison between real and estimated angles.

Table 4. Comparative table between the real and the estimated angles.

DS	Real angle θ	Real angle β	Estimated angle θ	Estimated angle B	Error θ	Error β
0.5	45	30	40.2	28.36	4.8	1.64
	90	70	86.34	65.89	3.66	4.11
	120	100	111.76	95.44	8.24	4.56
1	45	30	47.4	33.2	2.4	3.2
	90	70	85.56	72.41	4.44	2.41
	120	100	116.35	98.73	3.65	1.27
1.5	45	30	43.82	28.17	1.18	1.83
	90	70	86.91	65.3	3.09	4.7
	120	100	123.71	105.86	3.71	5.86
2	45	30	47.21	34.6	2.21	4.6
	90	70	88.94	73.64	1.06	3.64
	120	100	121.8	104.36	1.8	4.36
2.5	45	30	47.01	31.02	2.01	1.02
	90	70	91.2	68.53	1.2	1.47
	120	100	122.07	97.4	2.07	2.6
3	45	30	43.25	33.2	1.75	3.2
	90	70	86.47	68.76	3.53	1.24
	120	100	122.96	103.8	2.96	3.8

The angles are determined by applying geometric formulas (Equations (10), (12) and (13)). Once the angles are calculated, the direction and distance between the sensors and the source as well as the source position are estimated.

To evaluate the accuracy of our system Figure 6 shows the differences between the real angle and

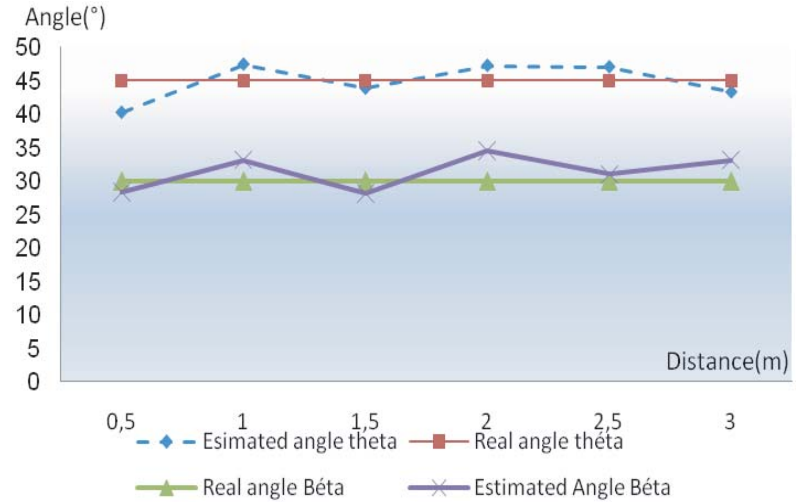

Figure 6. Example of differences between real and estimated angle.

estimated angle.

From Figure 6 we can deduce a small difference between real and estimated angles. The most common measure of an angle is in degrees. Figure 6 demonstrates the respective mean of estimated angle with 95% accuracy. It is noted that with audio localization approach, angle estimation was feasible with high precision.

The localization error is the distance between the real position of the source and its estimated position.

Let x_r, y_r and z_r be the real coordinates of the source and x_e, y_e and z_e the estimated coordinates. The localization error is determined as follows:

$$error = \sqrt{(x_r - x_e)^2 + (y_r - y_e)^2 + (z_r - z_e)^2} \tag{14}$$

Table 5 illustrates the 3D measurements of the positions of the source.

Table 5. Accuracy in function of error on the axis (x, y, z).

x_r	x_{es}	x_e	y_r	y_{es}	y_e	z_r	z_{es}	z_e
2.89	2.93	0.03	−24.2	−24.14	0.06	7.92	7.87	0.04
13.27	13.27	0.01	3.16	3.16	0.03	13.46	13.46	0.02
−20.49	−20.52	0.02	6.41	6.41	0.02	12.19	12.22	0.02
−1.19	−1.20	0.01	2.71	2.70	0.01	15.45	15.47	0.01
24.57	24.57	0.06	24.67	24.67	0.01	2.60	2.61	0.07
4.61	4.60	0.09	0.22	0.21	0.11	8.46	8.48	0.01
−5.54	−5.57	0.02	−32.30	−32.34	0.04	10.62	10.64	0.02
−3.68	−3.66	0.02	−4.00	−3.98	0.02	2.53	2.50	0.02
5.46	5.46	0.02	3.89	3.89	0.01	2.84	2.84	0.01
2.78	2.79	0.01	7.93	7.94	0.07	6.34	6.33	0.01

Figure 7 presents 3D wireless audio localization errors.

Simulation results show the localization error in our proposed schema of localization.

From Table 4, it can be observed that the error values are drastically reduced. This observation is graphically represented in Figure 7, where x-axis represents the number of iterations, and y-axis corresponds to the errors value of the localization.

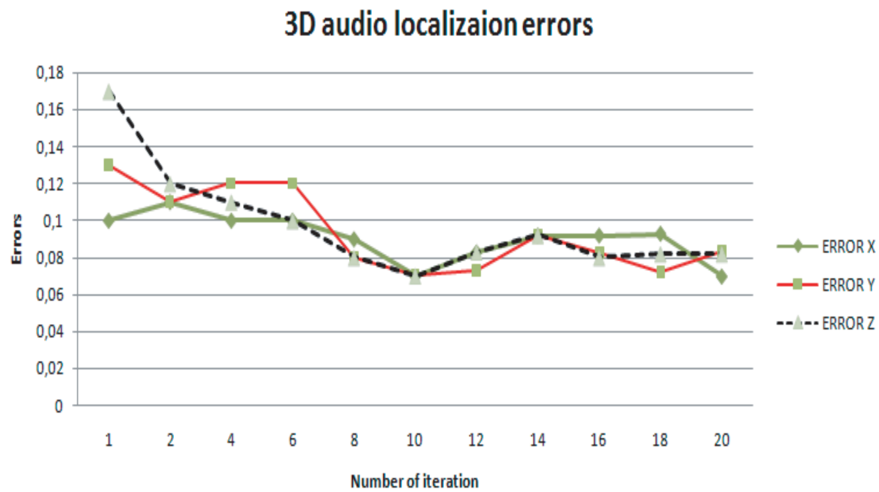

Figure 7. 3D audio localization error.

The proposed system provides location estimates of better than 6 cm accuracy. The proposed approach that uses audible band acoustic signals ($\leq$ 20 kHz) for propriety application can provide accurate estimations. However, an advanced signal processing is needed to improve the low power signal detection at the receiver.

Our audio localization systems have been shown to achieve high performance for indoor localization. Here we will compare our approach with recent research on acoustic-based 3D indoor localization.

The 3D FDM-PAM system presented in [29] can achieve positioning accuracy about 48.3 cm. Researches in [30] present a 3D location system using audible sound for positioning which works with an accuracy of about 9 cm in more than 97% cases. [31] presents a 3D acoustic system named Whistle based on synchronization-free TDOA framework for estimating of a target. The presented system [31] can achieve accuracy about 10 cm–20 cm. In [32], researchers develop a 3D-acoustic based fingerprinting localization approach achieving a resolution of 1 cm with 98% accuracy. Even with high accuracy, this approach causes unintended prediction errors when the phone is not placed correctly.

Although the proposed system utilizes only ordinary, inexpensive equipment, it provides accurate results as good as the ones offered by other systems.

4. 3D DEPLOYMENT BASED ON GENETIC ALGORITHM

4.1. Studied Problem

The problem studied in this paper is a Minimum Vertex Cover Problem. We want to find a minimum connected coverage of a network of audio sensors in a 3D grid of size $N * N * N$, each sensor being placed on a point of the 3D grid. The number of audio sensors must therefore be minimized.

4.2. Principle of Resolution

We want to implement an evolutionary algorithm to solve our problem. In this context, we will build a suite generation of solutions. Each generation will consist of admissible solutions S (individuals).

To move from one generation to the next, we use several bio-inspired operators:

i. Crossover.
ii. Mutation.
iii. Selection of individuals with the best qualities (here a minimum number of audio sensors).

When the termination condition has been reached, our generational process stops. We then refer to the best individual encountered during the iterations (in our case the space that has the fewest audio sensors).

- Initialization

In order to produce the first generation, we use a greedy heuristic.

The solutions are greedily generated from a 3D grid full of sensors and then removed one by one randomly until it is no longer possible to delete one without violating any constraints.

- Termination

As we have no prior information on the optimal solution of the problem, we base our stopping criterion on the stagnation of the optimal solution. If the best 3D grid encountered until then is unchanged for more than η generations, the algorithm stops, and this individual is returned. Choosing a high η gives us more guarantees about the optimality of the returned solution but also extends the computation time.

4.3. Implementation

In order to implement our approach, we will use an Object Oriented Language, namely C++.

Our program is based on three classes:

1. The class Case

This class is used to represent the content of each 3D grid position. The attributes of the class are:

- *audio*: Boolean indicating the presence of an audio sensor in a given position.
- *degreeCase*: integer giving the number of audio sensor in a specific radius.
- *neighbors*: list of positions (represented by a pair of integers), audio sensor capable of communicating with a given position.
- *mark*: Boolean used to mark the position (used for the route of the connection graph).

2. The class 3D Grid

This class is used to represent the 3D space that we want to cover with audio signal.
The attributes of the class are:

- *cases*: array of objects of the class case representing the 3D grid.
- *listAudio*: list of the positions (three attributes for the 3D grid) containing an audio sensor.
- *gauge*: integer evaluating the cost of a given 3D grid, in the case of a 3D grid connected it is therefore the number of audio sensor in the 3D grid, otherwise the gauge is worth N^2.
- *life*: integer giving the number of uses of the 3D grid to generate a new 3D grid (makes it possible to avoid that its genes are omnipresent in the different generations by erasing the 3D grid when its life exceeds a certain threshold).

The 3D Grid class has different methods for adding, removing, or adding sensor to a given position. A method for evaluating connectivity has also been implemented.

3. The Generation class

The objects of this class represent a tribe of S 3D grids. The attributes of the class are:

- *tribe*: array of size S containing 3DGrid objects.
- *Leader*: 3DGrid object, the best individual of the tribe.
- *vmin*: optimal obtained value.
- *year*: records the number of generations renewals.
- *stagnated*: gives the number of consecutive generation without improvement of the optimal value.

4.4. Simulation Results

In this part of our work, we implemented our model using "C++-MacOs". To validate our model, we started with an easy case study consisting of a one flower architecture characterized by the area of $10\,\mathrm{m} * 10\,\mathrm{m}$ presented in Figure 8. The optimized deployment obtained by our Genetic Algorithm gave the position of 5 audio sensors to guarantee the coverage of the studied space (Figure 9). We extended our simulation study for the case of 3D grid, for that we used a building with a total area of $10\,\mathrm{m} * 10\,\mathrm{m} * 10\,\mathrm{m}$ (Figure 10). The simulation study using the Genetic Algorithm allowed identifying the optimal deployment of the audio sensors (Figure 11).

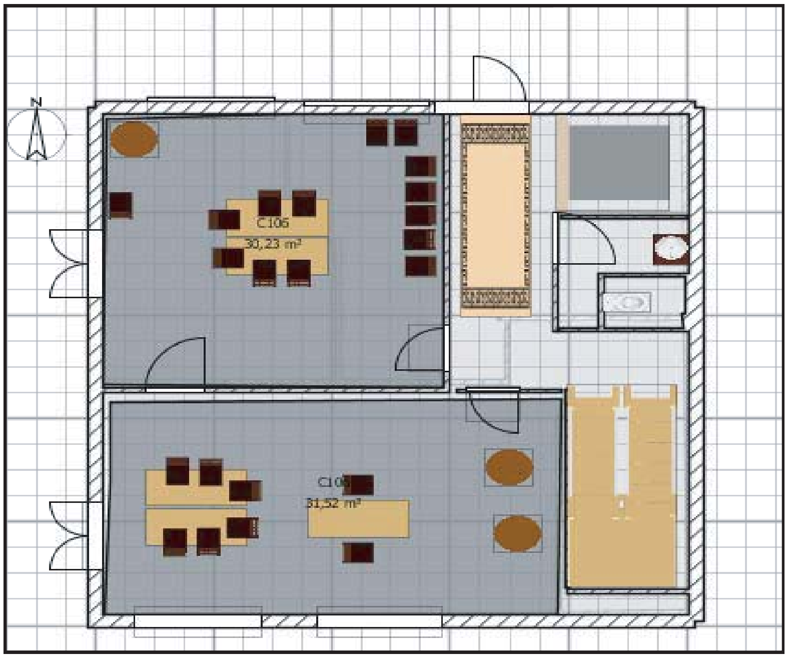

Figure 8. The 2D ground flower architecture for the real deployed indoor network (10 m $*$ 10 m).

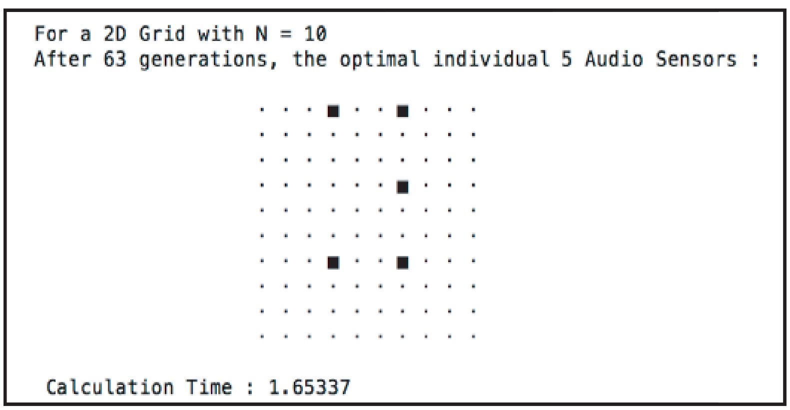

Figure 9. Genetic Algorithm for a (10 m $*$ 10 m) 2D Grid audio deployment.

Our study aims to model the notion of control and localization of a target in a context of a smart house. To give a real prototype we have extended our work to 3D modeling (Figure 10). This allows taking into account the 3D location of targets and the real-time monitoring.

Figure 11 shows the optimal positions of the audio sensors for 3D deployment while considering the coverage of the geographical area and the maximum range of the audio sensors.

Our approach using the Genetic Algorithm has resulted in an optimal number of audio sensors equal to 9 sensors allowing covering the total studied space

Based on the different experimental simulations we have deduced that the complexity of our algorithm is linear, and the needed time for the studied system is around 6 seconds. In the real life the target systems are similar to the chosen example in our paper.

Our algorithm is composed of an iterative structure from 1 up to n in which we have constant cost statements which conform the complexity $O(n)$.

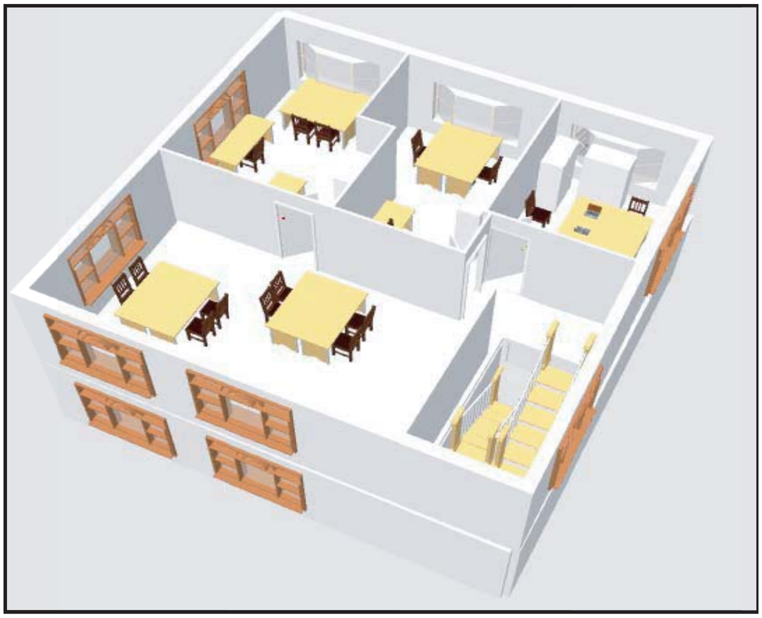

Figure 10. 3D architecture of the real deployed indoor network.

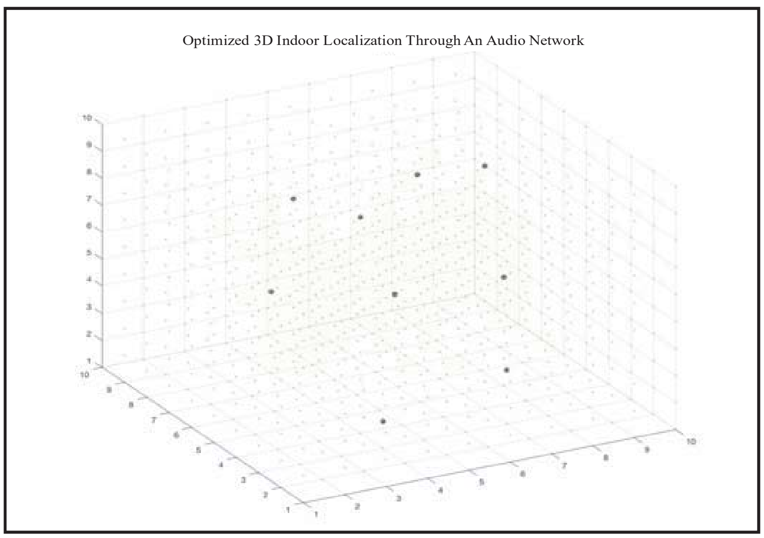

Figure 11. 3D Grid audio deployment based on Genetic Algorithm.

5. CONCLUSION

This paper presents an audio localization system based on the microphones network. The system is evaluated in a real scenario. A novel method is designed to derive the direction of the audio source by using TDOA parameters. Then a real-time precise localization and tracking are enabled by using a few anchor microphones with known locations.

The research has proved that the engineered methods for localizing audio events are capable of operating with adequate accuracy. It is possible to implement the methods in an environmental audio surveillance system, working in both indoor and outdoor conditions.

In addition, this paper provides a genetic algorithm-based approach to calculate the optimal placement of audio sensors in a novel 3D audio localization system.

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