Influence of Scalable Energy-related Sensor parameters on Acoustic Localization Accuracy in Wireless Sensor Swarms

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***Abstract*—Sensor swarms can be a cost-effectieve and more user-friendly alternative for location based service systems in different application like health-care. To increase the lifetime of such swarm networks, the energy consumption should be scaled to the required localization accuracy. In this paper we have investigated some parameter for energy model that couples localization accuracy to energy-related sensor parameters such as signal length,Bandwidth and sample frequency. The goal is to use the model for the localization of undetermined environmental sounds, by means of wireless acoustic sensors. we first give an overview of TDOA-based localization together with the primary sources of TDOA error (including reverberation effects, Noise). Then we show that in localization, the signal sample rate can be under the Nyquist frequency, provided that enough frequency components remain present in the undersampled signal. The resulting localization error is comparable with that of similar localization systems.**

I. Introduction

Technology is increasingly being used to help disabled or aging people maintain there independence. For example, by monitoring activity in a room, lights or the HVAC installation can be turned on or off to save energy. Another typical application of these ambient-assisted living technologies is fall detection. When someone is lying on the floor, this is detected and the emergency services are notified automatically. However, these systems typically rely on costly infrastructure like cameras. A more affordable alternative could be to use a "swarm" of cheap and relatively simple –often battery-powered– wireless sensors to monitor acoustic activity and distinguish between several events, e.g., fire or a cry for help [1], [2]

The main drawback here is the energy consumption of the sensors, which greatly reduces the lifetime of such networks (at least without replacing any batteries). The SINS research project aims to drastically improve both the lifetime and performance of the state-of-the-art of sensing swarms, with a focus on acoustic sensing.[1] When it comes to care homes and building monitoring applications, the acoustic sensor swarm should enable location based services, offering both acoustic event detection and source localization.

The work presented in this article is a part of the SINS project. More specifically, it covers the first steps of developing a sensor network, capable of supporting acoustic localization, and as such it can be seen as work in progress. With these first steps we want to explore the boundaries of our design in terms of localization accuracy, energy consumption and coupled parameters such as network throughput or ADC sample rate and resolution.[2] Furthermore, when the relation between energy consumption and localization accuracy is known, we can use this knowledge to design a model that estimates the accuracy and energy consumption for a give setting of the acoustic sensing system. This model can be used to drive a network application that scales the energy consumption of the network to the desired localization accuracy; i.e., the number of active sensors and their ADC settings can be changed by the network application. As research has shown, transmitting data takes the largest bite out of the energy budget of a wireless node [3], [5]. As such we will focus on the reduction of information being sent by the sensors and examine how this affects the localization accuracy.

We start the article with an overview of existing sound-based localization systems. This allows us to point out the differences with our approach. After that, in Section III, we discuss the requirements in terms of acoustic sensing when it comes to swarm-based localization. In that section we also present the MEMS microphone array that has been developed for our tests. In Section IV we explain our first measurements and we analyse the results. The final section concludes this article and states our future goals.

II. Related Work

In this section we give an overview of some existing systems that use audible acoustic sources as well as ultra sound as a means of localization. A more comprehensive review on existing indoor localization systems can be found in a survey by Hightower and Borrielo [6].

The two best-known localization systems that use ultrasound are *Active Bat* [7], [8] and *Cricket* [9]. *Active Bat* uses a Time-of-Flight lateration technique. It requires that users carry a tag equipped with an RF transceiver and an ultrasonic speaker. Base stations equipped with the same RF technology and

[1] SINS project webpage: http://www.esat.kuleuven.be/sins/

[2] The acoustic signals need to be digitalized with an Analog to Digital Converter (ADC) in order to process them and transmit them over the network.

ultrasonic microphones are mounted on the ceiling. For the positioning, the tag synchronizes with the base station via an RF signal and emits an ultrasonic pulse to a grid of ceiling-mounted receivers at the same time. Each wall sensor measures the time interval between arrival of the RF signal and the ultrasonic pulse, and computes its distance from the tag. *Active Bat* has been reported to achieve an accuracy of 9 cm in 95% of the cases. A drawback of this system is that the receivers need to be placed in a grid within a range of one meter.

Cricket also uses a combination of RF and ultrasound, but it has a different design strategy than *Active Bat*. In this system the beacons advertise their location to the tags (listeners) which are carried by the users. The beacon-listener synchronization is performed via RF. The mobile tags then use the ultrasound TOF measurement to determine their distance from every beacon. The tags perform lateration on three TOF measurements to get the absolute location.

Localization systems that use audible sound have also been developed. Scott and Dragovic [10] report a system for localization with finger clicks and hand clapping. The localization is performed by constructing a non-linear system of equations consisting Time-of-Arrival (TOA), microphone locations, and location of the sound source. The known variables are then substituted in the equation and the unknowns are calculated using a minimization algorithm. Their finger clicking experiment resulted in an accuracy of 27 cm over 90% of the cases.

Beep [11] is a positioning system which uses the wireless network and audible sound. The system consists of a set of acoustic sensor modules that are wirelessly networked and connected to a central server. The user's roaming device is assumed to have a wireless communication capability. When a user requests positioning, the user's roaming device synchronizes with the sensor nodes through the wireless sensor network. After this is done, the roaming device transmits a predetermined acoustic signal. The sensor detects this signal and makes an estimation of the Time-of-Flight and as such the distance between the sensor and the roaming device. These distances are then reported to the central server. The central server knows the precise location of each sensor and performs 3D multilateration to determine the coordinates of the roaming device. *Beep* has an accuracy of 60 cm in more than 97% of the cases.

BeepBeep [12] provides a highly accurate localisation system for mobile devices which is based on audible sound. The system uses no extra hardware and only requires specific software on the mobile devices. The localisation is done by a combination of two-way sensing, self recording and sample counting. Each device must emit a "beep" to estimate the distance between the two devices. This 'beep' will be received by both devices. Thus, each device receives two "beeps". One that has been transmitted by its own microphone and one that has been sent by the other device. By calculating the time difference between these "beeps", the Time-of-Flight can be estimated. This technology cancels delays and synchronization issues. *BeepBeep* has an accuracy of 2 cm in 98% of the cases.

Several articles have been published that describe acoustic localization with Angle Of Arrival (AOA) and triangulation [13]–[15].[3] However, most of these systems are mainly experimental. Since we will focus on TDOA-based localization in the remainder of this text, we will not discuss this topic any further.

[3]AOA is also often referred to as Direction Of Arrival (DOA).

III. System Development

A. Requirements

As stated in the introduction, this paper will focus on the development of a sensor swarm that is capable of supporting acoustic localization. To that end, we require an energy model that relates energy consumption to the sensors' configuration. We use the word "swarm" to indicate a high density heterogeneous wireless sensor network. This means that the sensors (i.e., acoustic sensors in our case) are separated about 10 m maximum. Furthermore, not all sensors have the same capabilities.

As we pointed out previously, most of the existing localization systems require that the source is equipped with either a microphone, a speaker (to send a predetermined sound), an RF transmitter or a combination of the aforementioned. It goes without saying that in many applications, where we want to determine the location of an unknown sound, this approach is not possible. This means that we can only do sound localization based on either Time-Difference Of Arrival (TDOA) or Angle Of Arrival (AOA) measurements.

From this observation follow some primary system requirements:

- For TDOA measurements, the audio streams of multiple sensors (at least 3) need to be combined. Consequently, the throughput of our network needs to be sufficient. In addition, the wireless sensors need to be synchronized in order to accurately determine the TDOA of a signal.
- In case of AOA measurements, the wireless sensors need to have a microphone array and sufficient processing power to compute angle and then angle will send to fusion center.
- In either case, the measurements need to be collected at a central processing system where the localization algorithm computes the position of the sound source.

Mainly the first to requirements will have an important influence on the energy consumption of the sensor network.

When we want the sensor network application to control the energy consumption, we need a model that selects the correct settings for the number of active nodes,the length signal (recording),spectrum of the signal,the sample frequency, ADC resolution, etc. To come to such a model we require data sets of acoustic measurements. In the next paragraphs we describe the design of a microphone array that is usable as acoustic sensing hardware for a wireless sensor. We will use this microphone array to collect the datasets that are required to make our energy model. In Section IV we describe our first measurements as well as our first results.

B. Microphone Array with Basic Off-the-shelf Components

For the acoustic sensing we developed a microphone circuit that can plug onto a wireless sensor module. That implies that a low-power microphone is required, as well as an amplifier circuit that boosts the microphone's signal level so that the ADC range is optimally utilized. Because most sensor

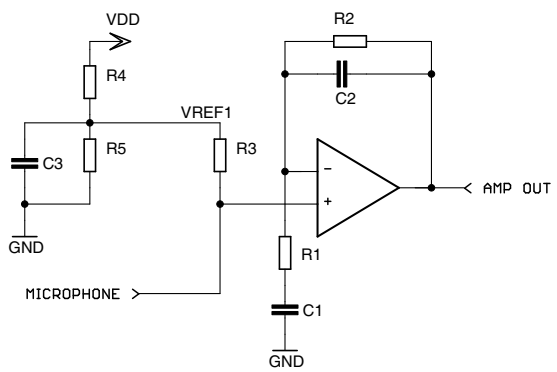

Fig. 1. Microphone amplifier schematic

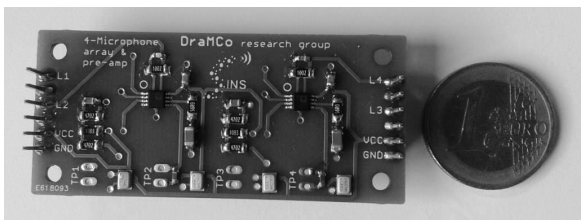

Fig. 2. Microphone array board. This board can be plugged on a sensor module or used separately. A coin of 1 Euro is shown next to it to indicate the size.

nodes run on batteries, the available voltage supply is 3.3 V maximum.
We opted to use a MEMS microphone because of its low energy consumption; specifically the Analog Devices ADMP504 [16]. The ADMP504 only draws 180 μA when powered. MEMS microphones are widely used in smartphones and tablet computers. We designed an amplifier circuit using a low-noise rail-to-rail operational amplifier –the Analog Devices ADA4896-2 [17]. This non-inverting amplifier circuit with asymmetrical voltage supply is shown in Fig. 1.

This circuit can operate from supplies ranging from more than 3.3 V to at least 2.0 V. Resistors R4 and R5 bias the signal to half the supply voltage (VDD), allowing for maximal drive. With the R1-C1 combination, we can select the band pass low frequency. Analogously, with R2-C2 we can select the high frequency. With the combination R1-R2, we can select the amplification. The current configuration has an amplification of about 45 dB in a band between 30 Hz and 20 kHz.
We have designed a printed circuit board with a microphone array of four ADMP504 microphones and their accompanying amplifiers. This microphone array can be plugged onto a sensor module or used separately. The assembled printed circuit board is shown in Fig. 2.

IV. First Measurements

The goal of these measurements is to collect data sets that can be used to create a model that relates localization accuracy to energy consumption. For this purpose the approach is decomposed in three parts. Firstly the data acquisition, i.e., reverberation or room impulse, recording high quality

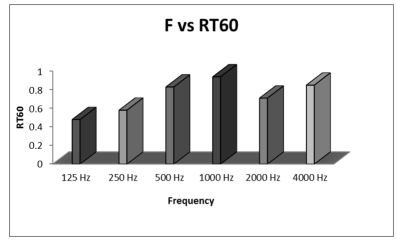

Fig. 3. Reverberation effect on frequency(ms).

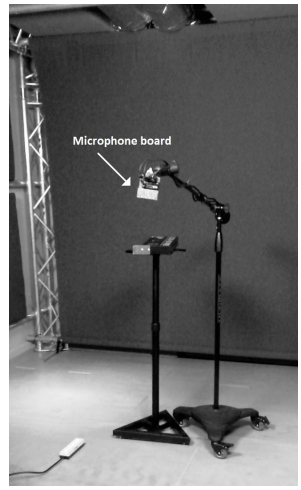

Fig. 4. Microphone board attached to a boom system.

sounds (with known characteristics), with synchronized recording channels. Secondly the signal processing and thirdly the localization accuracy tradeoff.

A. Data Set Collection

The measurements have been performed in the Nosey Elephant Studios,[4] which is the audiovisual laboratory of the Electronics Department of the VUB (Vrije Univeristeit Brussel). Next to the availability of professional recording equipment, there is the possibility to control room conditions like temperature and noise(Room dimension H2.67m x W4m x L6.67m, Single door (L1.8m x W0.9m, 53 STC) and a floating ceiling). For our measurement setup,we calculate reverberation effect based on frequency using Sabine equations shown in Fig. 3.So we can have feeling of reverberation effect.The noise floor (with HVAC on) was approximately 25 dB(A).
We attached the microphone boards to a boom system as shown in Fig. 4. Four of such booms have been placed on the corners of a 2-by-2 m square as shown in Fig 5.

As a sound source, we use a digitally created signal with known properties that is played through a speaker. The main reason why we take a signal with known properties is because this allows for easier modelling. For our first experiments we used a sine wave with a linearly increasing frequency between 200 Hz and 1.2 kHz and a duration of 1 second. The spectrogram of the signal is shown in Fig. 6. The signal output level has been selected by sending a 1 kHz signal to the

[4]Nosey Elephant Studios webpage: http://www.etro.vub.ac.be/research/Nosey_Elephant_Studios/index.asp

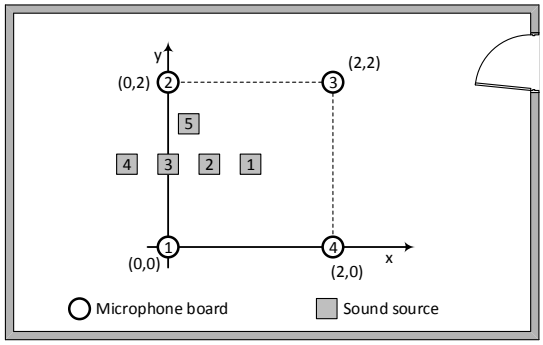

Fig. 5. Measurement setup.

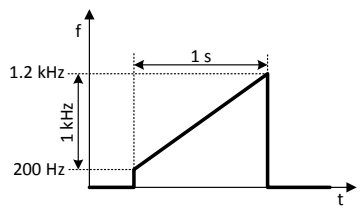

Fig. 6. Test sound spectrogram.

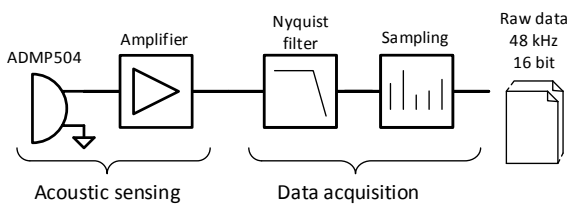

Fig. 7. Signal flow in the measurement setup. The acoustic sensing is done with our own microphone board. For the data acquisition we used the sound studio recording equipment.

speaker. We choose the highest signal level without distortion, when recorded by our microphone boards, i.e. an SPL (Sound Pressure Level) of 69 dB SPL.
The speaker (playing our test sound) has been placed at 5 different positions, as shown in Fig. 5. The test sound is recorded synchronously by the four microphone arrays with a sampling rate of 48 kHz and resolution of 16 bit. The signal flow in the measurement setup is shown schematically in Fig. 7.

B. Localization Algorithm

Currently, we only focus on TDOA-based localization. This means that we will use only one channel per microphone array, i.e. we mimic a sensor module with a single microphone. The implementation of the localization algorithm starts with reading the recorded data. The TDOA between the reference channel (i.e., the signal recorded by microphone board 1) and any other channel, is typically computed by finding the delay that causes the cross-correlation between the two signals segments to be maximum for a given time segment.

A TDOA value does not show any useful information when it is computed over a silence or when the SNRs of the signals

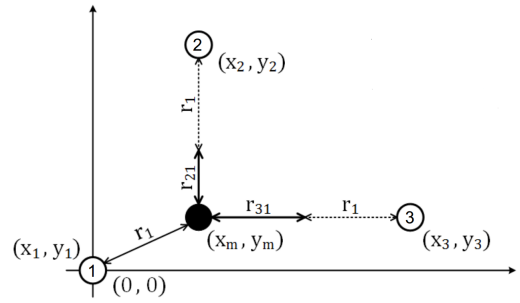

Fig. 8. Principle of two-dimensional TDOA-based multilateration.

(either one) are very low. The problem was addressed by using a function that splits the sound prior to any further processing. In this way, only the segments of the recording that contain sound are being processed by our localization algorithm.
In order to improve robustness against reverberation we use the Generalized Cross Correlation with Phase Transform (GCC-PHAT) as presented by Knapp and Carter [18] and Brandstein and Silverman [19]:

$$\hat{G}_{PHAT}(f) = \frac{X_i(f)\,[X_j(f)]*}{\left|X_i(f)\,[X_j(f)]*\right|} \quad . \tag{1}$$

Where $X_i(f)$ and $X_j(f)$ are the Fourier transforms of the two signals and * denotes the complex conjugate.

The TDOA $\hat{t}_{PHAT}(i,j)$ for two channels i and j is estimated as:

$$\hat{t}_{PHAT}(i,j) = \arg\max_t \hat{R}_{PHAT}(t) \quad . \tag{2}$$

Where $\hat{R}_{PHAT}(t)$ is the inverse Fourier transform of Eqn. 1. The computation of the TDOA between each pair of microphones is repeated along the recording for every time segment containing sound. In addition, post-processing steps, like post-filtering algorithms, can be used to improve the TDOA algorithm's accuracy and to make it more stable. However, they have currently not been considered. After the algorithm finds the TDOA values, it converts them to the corresponding distance, taking into account the speed of sound (v).

The so-found distance differences, together with the coordinates of the sensors, can be used by a multi-lateration algorithm to estimate the position of the sound source. The operation of the algorithm we use, is briefly explained in the following paragraphs. Currently only a two-dimensional variant has been implemented.

The algorithm starts from a situation as exemplified in Fig. 8. The reference channel is assumed to be in the origin and as stated in the previous paragraphs, the distance difference r_{ij} can be computed from the TDOA: $\hat{t}_{PHAT}(i,j) \cdot v$. The coordinates of the sound source are denoted (x_m, y_m).

This situation can be expressed as a system of 2 unknowns[5]

[5]Only x_m and y_m are unknown as $r_1^2 = x_m^2 + y_m^2$, but writing it like this simplifies the equations.

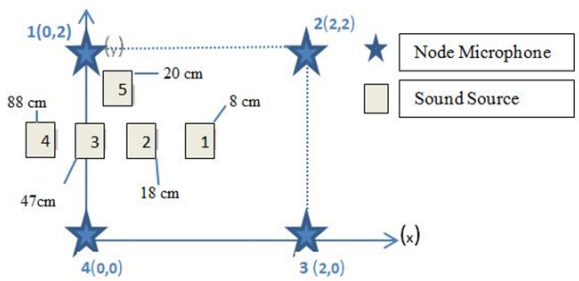

Fig. 9. Average localization error [cm] for each position of the sound source.

and at least 2 equations (matrix form):

$$\begin{bmatrix} x_2 & y_2 & r_{21} \\ x_3 & y_3 & r_{31} \\ & \dots & \\ x_n & y_n & r_{n1} \end{bmatrix} \cdot \begin{bmatrix} x_m \\ y_m \\ r_1 \end{bmatrix} = \frac{1}{2} \begin{bmatrix} K_2^2 - r_{21}^2 \\ K_3^2 - r_{31}^2 \\ \dots \\ K_n^2 - r_{n1}^2 \end{bmatrix} \quad . \tag{3}$$

with $K_i^2 = x_i^2 + y_i^2$

Equation (3) formulated briefly:

$$Hx = d \ . \tag{4}$$

We find the least-squares estimation $\hat{x}$ of x by computing:

$$\hat{x} = \left(H^T H\right)^{-1} H^T d \ . \tag{5}$$

This is a variation on the technique presented in an iterative algorithm with least square fits to approximate the solution in a stepwise manner (A. Kpper). [20]. The main difference is that our approach requires no prior knowledge of r_1.

C. Results and Analysis

As stated in previous paragraphs, if we can use small segment of a signal so node will consume less power, reducing the sample frequency and Bandwidth will result in a lower energy consumption in the wireless sensor swarm. Based on the recorded high-quality signals (48 kHz sample frequency, 16 bit resolution), we have created low-quality signals as if they were sampled by such a swarm network with a lower sample frequency and resolution. We have done this for sample frequencies of 48, 16, 8, 4, 2 and 1 kHz and ADC resolutions of 16 bit(different resolution don't have influence) [4]. We have used the algorithms reviewed in the previous paragraphs to perform localization based on these signals and we have evaluated the resulting localization accuracy.

The first striking result is the influence of the position on the localization. In Fig. 9 we show the localization error for each position of the sound source. The exact coordinates of the sound source are listed in Table. I. It is clear that the error is much lower for positions that are inside the grid ($<$ 20 cm). Moreover these errors are comparable with the results from [10], [11], i.e., two systems that use audible sound without two-way ranging.

In bar graph shown in Fig. 10, we show the localization error [cm] for position 5, i.e., a random position inside the grid, for each combination of recorded signal(duration of 1,2,5 sec)but different spectrum(50,200,1000 Hz). It is clear that

TABLE I. COORDINATES OF THE SOUND SOURCE [M] FOR EACH POSITION.

Position	x	y
1	1	1
2	0.5	1
3	0	1
4	-0.5	1
5	0.36	1.46

signal length doesn't affect the localization and also bandwidth has small influence show in Fig. 11.The main reason is that the signal length (duration of 1,2,5 sec) has enough sample to measure cross spectrum to find distance. But spectrum has a influence as we know higher frequency has more reverberation effect. In that regard, it might be interesting to examine how shorter we can go?.

In bar graph shown in Fig. 12, we show the localization error [cm] for position 5, i.e., a random position inside the grid, for each combination of sample frequency and resolution that we have considered. It is clear that for sample frequencies above the Nyquist frequency (in our case 2.4 kHz; the four bar in Fig. 12, the resolution does not affect the localization. We need to note, however, that the speaker volume was set to maximum level without distorting the recorded signal. In that regard, it might be interesting to examine the effect of the resolution when the SNR gets lower and if microphone amplifiers with automatic gain control can contribute to keeping the required resolution low.

The best localization results are found for 2 kHz (this is also the case for the other positions). The main reason is that the recorded signal will contain less noise compared to the oversampled recordings. However, we need to note that we currently don't use any noise reduction techniques on the oversampled signals. While 2 kHz is slightly under the Nyquist frequency of our test signal (some frequency components will hence be filtered out), it still contains enough information to be used for localization. When the sample frequency is to low, however, the localization fails, as is the case for a sample frequency of 1 kHz. When sampling close (and under) the Nyquist frequency, the resolution seems to be of influence. In our setup we require at least 8 bits. Hence, an audio stream of at least 16 ksamples/s per node is required. Keep in mind that, audio compression techniques can be used to further lower the transmitted data rate.

V. CONCLUSION

This article covers the design of a wireless sensor swarm for acoustic localization, mainly the few steps in developing an energy model. To perform realistic measurements, a MEMS microphone array has been developed that can either be used separately or plugged onto a wireless sensor module.

A test setup for two-dimensional localization has been used to record signals that are representative for a wireless sensor network application. Using these data, the effect of the sample frequency and ADC resolution on the TDOA-based localization error has been investigated. Choosing an appropriate signal length, Bandwidth,sample frequency and resolution, yields a localization error that is comparable with that of similar localization systems. More interestingly, the

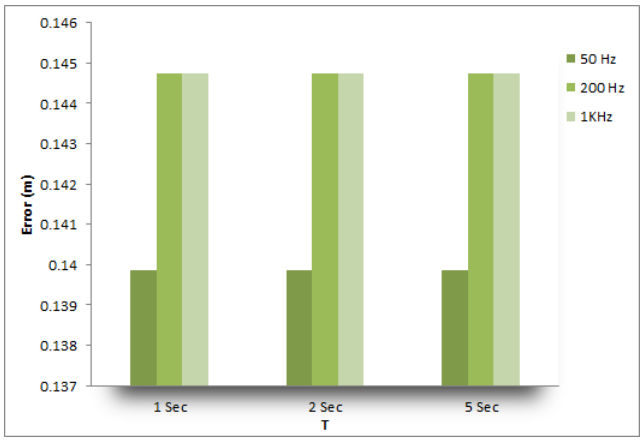

Fig. 10. localization error [cm] for a given duration.

Fig. 11. localization error [cm] for a given duration.

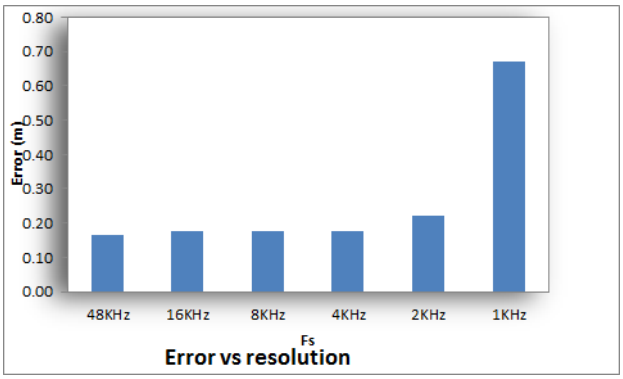

Fig. 12. Average localization error [cm] for a given sampling frequency.

sample frequency can be under the signals Nyquist frequency, provided that enough frequency components remain present in the undersampled signal. This can significantly reduce the energy consumption.

Since this is a report of our work in progress, we can briefly list some of the parameters that we want to incorporate in our model. First of all the number of sensors (TDOA-values) that is used in the localization as well as the influence of the distance between the sensors, has not been considered. Secondly, the wireless sensors have the capability to do some preprocessing on the audio streams before sending them to the wireless network. Digital noise reduction (with over sampled signals) can improve the localization accuracy whereas audio compression can reduce the required data bandwidth. Thirdly, the localization of multiple sound source will have to be investigated as well.

Next to modelling TDOA-based localization accuracy (and required energy consumption) we will have to consider AOA-based localization as well. Finally, the model should be validated in a real-life setup so the reduction of the energy consumption can be evaluated.

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