Self-localization of Dynamic User-Worn Microphones From Observed Speech

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Abstract

The increase of mobile devices and most recently wearables has raised the interest to utilize their sensors for various applications such as indoor localization. We present the first acoustic self-localization scheme that is passive, and is capable of operating when sensors are moving, and possibly unsynchronized. As a result, the relative microphone positions are obtained and therefore an ad hoc microphone array has been established. The proposed system takes advantage of the knowledge that a device is worn by its user e.g. attached to his/her clothing. A user here acts as a sound source and the sensor is the user-worn microphone. Such an entity is referred to as a node. Node-related spatial information is obtained from Time Difference of Arrival (TDOA) estimated from audio captured by the nodes. Kalman filtering is used for node tracking and prediction of spatial information during periods of node silence. Finally, the node positions are recovered using multidimensional scaling (MDS). The only information required by the proposed system is observations of sounds produced by the nodes such as speech to localize the moving nodes. The general framework for acoustic self-localization is presented followed by an implementation to demonstrate the concept. Real data collected by off-the-shelf equipment is used to evaluate the positioning accuracy of nodes in contrast to image based method. The presented system achieves an accuracy of approximately 10 cm in an acoustic laboratory.

Keywords: Self-localization, ad hoc networks, microphone arrays, acoustic measurements, kalman filtering, data association

1. Introduction

Self-localization is one of the enabling technologies in acoustic sensor networks. The self-localization means that the physical locations of the nodes are determined automatically. This enables fast deployment of such a network for spatial applications e.g. sound source localization via TDOA \cite{1}|\cite{2}|\cite{3}|\cite{4} and audio enhancement via spatial filtering techniques, such as beamforming \cite{5}, which traditionally rely on node geometry and temporal synchronization of microphones. Higher-level applications that can utilize the self-localization as underlying technology include automatic meeting transcriptions \cite{6} and providing aid for hearing impaired persons by signal enhancement \cite{7} \cite{8}.

The increase of smart technology embedded into mobile phones, tablets, wrist watches, fitness bands, apparel, and jewellery has created a need for self-localization of the networks created by the sensors of the devices. Once the sensors are self-localized, they can be used for various tasks including the ones mentioned above. There are many challenges in taking such ad hoc sensor networks to use. The devices in general are different, and the quality of microphones analog-to-digital converters may vary significantly\textsuperscript{1}. Furthermore, there may be unpredictable processing delays in audio path.

To be transparent and easy to adapt for many applications, and to be equipment agnostic, the self-localization must take place without extra hardware components or the use of intrusive signals. Furthermore, the most versatile form of self-localization and synchronization is applicable even after the capture event. This basically means using the environmental sounds in self-localization from unsynchronized audio streams. So far, this level of performance has been achieved in a scenario with static device \cite{9}|\cite{10}. Furthermore, in the user-worn microphone scenario, the self-localization must take the node motion into account, and therefore continuous self-localization is needed.

In this article we present an acoustic self-localization method for the dynamic sensor scenario in 3D space where the nodes of the acoustic sensor network are continuously changing their places. The node positions are calculated from the speech signal produced by the nodes themselves. Each node contains a microphone \textit{m} and a source \textit{s} (see Figure 2).

The proposed method extends the previous work of \cite{10}|\cite{11} by allowing the nodes to be in motion while estimating their position from the audio produced by the

\textsuperscript{1}In this work homogenous hardware is used and it is acknowledged that future work should include research with heterogeneous hardware.
nodes themselves. The data streams recorded by the nodes are unsynchronized, which is completely different from using wireless microphones that can utilize radio frequencies for side channel synchronization. The real data recordings using off-the-shelf hardware are used to evaluate the proposed system. The evaluation is made by comparing the estimated node paths to the reference node paths obtained from an implemented multiview camera setup.

This article is organized as follows. Section 2 reviews background of passive acoustic self-localization. Section 3 presents the theory of the proposed system. Section 4 describes how the theoretical presentation is implemented. In Section 5 the measurement procedure is described. Section 6 presents the performance evaluation procedure. In Section 7 clock drift analysis of the used equipment is presented. Section 8 presents real data performance of the proposed system. Section 9 discussion about the results and further development of the system is provided. Section 10 concludes the article.

2. Background

The general self-localization problem of acoustic sensor networks is stated as solving the positions of the nodes of the network. The network in general consists of sensors (microphones) and sound sources. Usually, the sensor positions are of interest in self-localization, but once they are obtained, sound sources can be localized if desired using e.g. multilateration. The general self-localization problem is solved by the following minimization problem (see [12])

\[ J(\mathbf{S}, \mathbf{M}, \mathbf{\alpha}) = \min_{\mathbf{S}, \mathbf{M}, \mathbf{\alpha}} \sum_{i,j,k} \left( c^{-1}(\|s_k - m_i\| - \|s_k - m_j\|) + \alpha_i - \alpha_j - r_{ij}^k \right)^2, \]

where the sum is over all \( k = 1, \ldots, K \) sound sources and \( \frac{N(N-1)}{2} \) unique microphone pairs \( (i,j) \). \( \mathbf{S} = [s_1, \ldots, s_K]^T \) and \( \mathbf{M} = [m_1, \ldots, m_N]^T \) are matrices whose columns are the Cartesian coordinates of sensor and microphone positions, respectively. \( \mathbf{\alpha} = [\alpha_1, \alpha_2, \ldots, \alpha_N]^T \) are temporal offsets of the sensors, and \( c \) is the speed of sound. \( r_{ij}^k \) is TDOA measured by sensor pair \( i,j \) from sound source \( k \). The global minimum of (1) can be interpreted as correct positions of sound source positions, microphone positions, and temporal offsets of the captured audio.

Especially, with increasing number of sensors and sound sources (1) becomes an optimization problem plagued by local minima. Furthermore, any solution of (1) is subject to transformations that preserve distances between two points, such as translation, rotation, and reflection. In 3D space, the set of such transformations is referred to as the Euclidean group 3, \( \text{E}(3) \) [13]. This means that even the global optimum of (1) may differ from physical ground truth node coordinates.

In [14] a self-localization method based on time-of-flight and time-difference-of-flight is presented. Multidimensional Scaling (MDS) [15] is used to initialize the optimization problem (similar to (1)). The method also estimates temporal offsets for each node. The method assumes that nodes have capability to emit and receive sounds unique to each node and estimates pairwise distance matrix (corresponding to \( r \) above).

In [16] a Time of Arrival (TOA) based self-localization method is presented. TOA is estimated from sounds naturally occurring in the environment. The synchronization of the receivers is crucial for the method and therefore it has a side-channel and infrastructure for it.

In [17] is a matrix factorization method and it attacks the general self-localization problem by dividing it into a sequence of simpler problems to avoid getting stuck to local minima. The general self-localization is eased by assuming that sound events occur in far field with respect to receivers, which enables to the simplification of the optimization problem. The resulting constraint of the simplified optimization problem is used to obtain the positions of the receivers. An extension of [17] is presented in [18] which takes measurement uncertainty into account. In near field, a rank-5 factorization method is needed [19] which requires at least ten microphones and four sources or vice versa. The methods [17], [18], and [19] expect synchronous audio streams.

A method presented in [20] is directed to microphone array self-localization or calibration in diffuse soundfield. An extension to [20] is presented in [21], which uses multiple arrays and sound source localization to estimate relative rotation and translation of an array pair. Both methods are designed for relatively small intra-sensor distances of approximately 20 cm or smaller.

In [22] a method for ad hoc sensors is presented. The method is able to estimate the relative smartphone positions from measured TDOA. Pairwise sensor distances are estimated and MDS is performed to obtain the initial positions to an optimization problem similar to (1). Furthermore, four of all the variables in the optimization problem are fixed to establish a coordinate system (2D case). The method requires known calibration signals, which are audible and in frequency range from 5 kHz to 16 kHz. Another system using active calibrations signals is presented in [9]. The system performs direction of arrival estimation and distance estimation for self-localization.

In [23] a self-localization method of moving receiver based on TDOA estimation from ultrasound is presented. Using frequencies outside human hearing is attractive due to unobtrusiveness. The drawback of the system is requirement of an infrastructure of ultrasonic transmitters, their careful placement in a room, and side channel for data association.
3. Theory

The general idea of an acoustic self-localization system in user-worn devices scenario is presented in Figure 1. Like in [10],[11] the fundamental idea is that the system estimates pairwise distances between all the nodes in the network. From pairwise distance matrix relative coordinates can be estimated by finding node geometry in the Euclidean space that fulfills the restrictions of the distance matrix. The novelty is in proposing a tracking of the distance matrix, which allows self-localization of moving nodes continuously in contrast to [10],[11]. The theoretical presentation of each subsystem illustrated in Figure 1 is given in this section.

3.1. Signal Model

Let \( \mathbf{m}_i \in \mathbb{R}^3 \) be the \( i \)th node position and \( i \in 1, \ldots, N \). In an anechoic room the signal \( m_i(t) \) can be modeled as a delayed source signal \( s_k(t) \) as

\[
m_i(t) = s_k(t - \Delta^k_i) + n_i(t),
\]

where \( t \) is time, \( k \in [1, \ldots, N] \) denotes active node index with \( N \) nodes, \( n_i(t) \) is noise component, and \( \Delta^k_i \) is TOA from active node \( k \) to the \( i \)th node

\[
\Delta^k_i = c^{-1} \| s_k - \mathbf{m}_i \| + \alpha_i,
\]

where \( \alpha_i \) is unknown time offset, \( c \) is speed of sound, and \( s_k, \mathbf{m}_i \in \mathbb{R}^3 \) are source and microphone positions.

3.2. Spatial information: TDOA and TOA

Clearly, the position of each node is characterized by TOA. However, TOA can not be measured directly in the passive self-localization problem, but the differences between each node pair TOA, that is Time Difference of Arrival (TDOA), can be estimated. TDOA between microphone pair \( \{i, j\} \) for source \( k \) is

\[
\tau_{i,j}^k \triangleq \Delta^k_i - \Delta^k_j = c^{-1}(\| s_k - \mathbf{m}_i \| - \| s_k - \mathbf{m}_j \|) + \alpha_{ij},
\]

where pairwise time offset is \( \alpha_{ij} \triangleq \alpha_i - \alpha_j \). The time offsets result from the fact that in an ad hoc network nodes have their own time axis. Furthermore, analog-to-digital converters of devices have clock drift, which has to be taken into account if the drift is several samples over a time period comparable to the analysis window length used by the self-localization method.

In [24] it is noted that TDOA can be formulated as the matrix product of an observation matrix \( H \) and TOA vector \( \Delta \). In the formulation below, we ignore superscripts for clarity.

\[
\tau = H \Delta,
\]

where \( \tau \) is the TDOA vector, \( \Delta = [\Delta_1, \ldots, \Delta_N]^T \) is the TOA vector, and \( H \) is the observation matrix.

\[
H = [e_1 - e_2, e_1 - e_3, \ldots, e_1 - e_N, e_2 - e_3, \ldots, e_2 - e_N, \ldots, e_{N-1} - e_N]^T,
\]

where \( e_i = [\delta_{i1}, \ldots, \delta_{IN}]^T \), where \( \delta_{ij} \) are Kronecker’s delta function.

Equation (5) can be solved for \( \Delta \) using the Moore-Penrose pseudoinverse. However, the columns of the measurement matrix \( H \) are linearly dependent and its rank is equal to \( N - 1 \). To address this issue, the first column of \( H \) is removed and the corresponding TOA can not be solved, but can be set as reference \( \Delta_1 = 0 \). The TOA values \( \Delta_i, i = 2, \ldots, N \) are relative to \( \Delta_1 \). The pseudo-inverse TOA estimator is [24]

\[
\Delta_0 = H_0^+ \tau,
\]

where \( H_0^+ = (H_0^T H_0)^{-1} H_0^T \) and \( H_0 \) is otherwise the same as the observation matrix \( H \) but the first column removed. The resulting TOA vector is written \( \Delta_0 = [\Delta_2, \ldots, \Delta_N]^T \) and thus the number of TOA estimates is \( N - 1 \) per a time frame.

3.3. Active Node Detection, Data Association and Tracking

In spatial signal processing it is often important to be able to detect and track sources. In case of one target, the tracking can be based on a linear Gauss-Markov system, which can be implemented as the Kalman Filter [25]. With non-linearities present (e.g. in measurement model), Extended Kalman Filter (EKF) [26] and Unscented Kalman Filter (UKF) [27] can be used. A fundamental problem in single target tracking is to distinguish actual measurements from clutter. In case of multiple targets, besides clutter detection, a data association scheme has to be introduced, that is, assigning each measurement to a correct target, initializing new targets and deleting old ones. This known as Multiple Target Tracking (MTT) problem. A variety of solutions to MTT have been presented over the years. Nearest neighbor Kalman Filter (NNKF) [28] assigns an input within the smallest statistical distance to the predicted value. The measurements outside
Multiple nodes \( N > 1 \) form an ad hoc network, to which the theory can be applied, and \( N = 1 \) is trivial.

4.2. Input

The system processes input data in frames of size \( L \) samples, that is, the input signal is a windowed version of audio stream \( m_i(t) \) captured by each node \( i \) (hereafter, \( t \) refers to a frame index rather than a single sample). The sampling rate is 48 kHz and the window length \( L = 8192 \) (\( \approx 170\) ms). A longer window helps to integrate over phonemes for more frequency content, but stationary assumption favors shorter windows. A compromise between these properties was made. Sequential windows are overlapping in time by 50 \% and Hann window function is used [32].

The DFT is calculated and the microphone data in the Fourier domain is denoted by \( X_i(t, \omega) \). The data used in this article contains recordings with four nodes\(^2\) therefore the number of audio channels \( N = 4 \).

4.3. TDOA Estimation

TDOA estimation can be done using Generalized Cross Correlation (GCC). GCC is often used with a weighting function such as Phase Transform (PHAT) (see [31]). Theoretically, PHAT makes the correlation function an impulse function, where the impulse occurs at the time instant corresponding to the temporal delay between the signals. In practice, cross correlation function calculated between two audio signals has several peaks resulting from echo and noise sources. PHAT weighting lowers the peaks caused by indirect path propagation [33]. The cross correlation function in time frame of length \( L \) samples microphone pair \( i, j \) is written

\[
r_{ij}(t, \tau) = \sum_\omega \Phi(t, \omega) X_i(t, \omega) X_j^*(t, \omega) \exp(j \omega \tau),
\]

where \( \Phi(t, \omega) = |X_i(t, \omega) X_j^*(t, \omega)|^{-1} \) is the PHAT weighting function [31]. \( X_i(t, \omega) \) denotes Discrete Fourier Transform (DFT) of input signal frame length of \( L \). \(^*\) denotes complex conjugation, \( \tau \) is the time delay, and \(|.|\) denotes absolute value. NB: \( j \) in \( \exp(j \cdot) \) refers to imaginary unit rather than node/microphone index.

The TDOA estimate is obtained by searching the maximum of the correlation function:

\[
\hat{\tau}_{ij}(t) = \argmax_\tau r_{ij}(t, \tau).
\]
4.4. Data Association and Tracking

4.4.1. Data Association

The data association and tracking method used in this work exploits the geometry of user-worn devices: each node contains a microphone and a source. Therefore, it is highly likely that the loudest speech energy that exceeds background noise energy level can be detected in the nearest microphone where the source is active at current time. At 20 cm distance from mouth an average Sound Pressure Level (SPL) of 72 dB for normal speech has been reported. In free field, the same speech level at 1 m distance would result in 58 dB SPL [34]. However, it is possible to measure high levels that are originated from other nodes in certain situations. Such false positives could result from e.g. two nodes are located near to each other. Additionally, it is possible that some other sound causes SPL that exceeds the level of speech. In this work the issues above are addressed by assuming that there is only one source active at a time and the content of test data contains mainly signal originated from mostly speech source. We found that the simple SPL threshold for source detection and identification was robust enough. However, more sophisticated data association [30] and speech detection methods [35] could be applied in more complex scenarios than presented here.

The signal energy corresponding node $i$ in time frame $t$ is written

$$E_i(t) = \sum_{l=(t-1)L+1}^{(t+1)L+1} m_i^2(l). \quad (10)$$

The active source index $j(t)$ is estimated by search the maximum energy level among the nodes $i = 1, \ldots, N$:

$$j(t) = \arg \max_i E_i(t) \quad (11)$$

4.4.2. Tracking

The tracking of TOA estimates is implemented as the Kalman Filter (KF) [25]. The use of Kalman filtering in TOA tracking was presented in [24]. Each node has its own Kalman Filter (see Figure 3) and the KF that receives the measurement in time $t$.

The state transition matrix is written

$$A = \begin{bmatrix} 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta t & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta t \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}_{6 \times 6} \quad (15)$$

and the observation matrix (5) is

$$H_0 = \begin{bmatrix} -1 & 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 & 0 \\ 1 & -1 & 0 & 0 & 0 \\ 1 & 0 & -1 & 0 & 0 \\ 0 & 1 & -1 & 0 & 0 \end{bmatrix}_{6 \times 6} \quad (16)$$

The tracked TOA estimator in frame $t$ is obtained from the state vector $x(t)$ indices 1, 2, and 3 as follows. $\Delta(t) = [0, x_1(t), x_2(t), x_3(t)]^T$.

4.4.3. Pairwise Distance and Relative Coordinate Estimation using MDS

The TOA estimates are converted to TDOA:

$$\tau_{ij} = \Delta_i - \Delta_j. \quad (17)$$

Using the apriori knowledge of sound speed $c \approx 344 \frac{m}{s}$ in indoors, TDOA information can be transformed into a single pairwise distance matrix $D$, which is written as

$$D = \begin{bmatrix} 0 & d_{12} & \cdots & d_{1N} \\ d_{21} & 0 & \cdots & d_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ d_{N1} & \cdots & d_{N,N-1} & 0 \end{bmatrix}_{N \times N} \quad (18)$$

where $d_{ij} = c \cdot \tau_{ij}$.

The distance matrix can interpreted as scalar product matrix [15, Chapter 7.9]:

$$D = OO^T, \quad (19)$$

where $O$ is an $N \times D$ matrix, where $N$ is the number of points in $D$ dimensional space [15]. Here, the rows of $O$ are the relative 3D coordinates of $N = 4$ nodes. The eigendecomposition of $D = C\Lambda C^T$ can be expanded to $D = (C\Lambda^{1/2})(C\Lambda^{1/2})^T$, where $\Lambda^{1/2}$ is a diagonal matrix. The diagonal elements $\lambda_i$ are square roots of eigenvalues of $D$. Scalar product matrices are symmetric and have nonnegative eigenvalues [15]. Let us denote $\Omega = C\Lambda^{1/2}$.

Clearly, $\Omega = C\Lambda^{1/2}$ reconstructs $O$ in (19). 3

\(^3\text{Matlab function \texttt{mdscale} implements MDS algorithm and is used here with \texttt{cmdscale} option on to estimate relative coordinates from the estimated distance matrix.} \)
The temporal offsets of the nodes can be estimated from tracked TDOA estimates using the method proposed in [11]. However, the self-localization of the nodes is targeted in this work and moving node offset estimation in this scenario is left for future work.

5. Measurements

This section describes the measurement scenario, environment, the reference data capture framework and its calibration, and scoring of acoustic estimates.

5.1. Measurement Scenario

In each scenario there are four nodes and the goal is to estimate each node’s position. The scenario in which nodes are moving is referred to as dynamic phase. Each recording consists of calibration phase and dynamic phase. During the calibration phase the nodes are stationary and each node sequentially emits an approximately five seconds of speech. The calibration phase is in the beginning of each recording and during it the initial positions of the nodes are estimated. The method to obtain the initial positions is presented in [9], which performs self-localization for non-moving nodes by assuming that a sound is observed from every node. The method of [9] is designed to operate with TOA, whereas the proposed system estimates TDOA, therefore so called relative TOA\(^4\) is estimated using one microphone as a reference (see Section 3.2). The calibration phase is mandatory for the proposed system to operate in dynamic phase.

During dynamic phase two nodes are in motion. While moving the nodes sequentially emit an approximately five seconds of speech. The two other nodes are stationary over the whole recordings. In dynamic phase, the planned path for node 3 is to move towards node 4 (stationary node), then towards node 2 (moving node) starting position and turn back using the same path. We refer to this as node sequence. The planned route for node 3 is illustrated in Figure 6a. Node 2 moves simultaneously and its node sequence is 1, 2, 3, 1, 2. As an example, the actual path of node 3 in Recording 1 is illustrated in Figure 6b with red dots obtained from annotated pixels converted into room coordinates using the transformation presented in Section 5.5. The "saw-tooth" like movement of node 3 results from gait of a person. Figure 6c presents the activity pattern in Recording 1. The activity patterns are similar in all the recordings. Note that the proposed method is not limited to two moving nodes, but all nodes can be in motion after the calibration phase. The choice to use two moving nodes in the measurements was made for practical reasons.

\(^4\)as is typically used to steer a beamformer

5.2. Recording Room Description

Each recording was made in a room with dimensions 4.5 m \(\times\) 3.9 m \(\times\) 2.6 m. Four video cameras were attached to the room corners to gather reference video data, which is manually annotated for smartphone positions (in image coordinates). The view from each camera can be seen in Figure 5 and the room plan in Figure 6a. The room can be characterized as low reverberant room \(T_{60} = 260\) ms. Some of the flat surface area (part of the ceiling and part of the walls) is covered with sound absorbing material. However, the room is much more reverberant than a half-anechoic chamber. The air-conditioning produced low noise during the data capture.

5.3. Recording Equipment

Each node is equipped with a Nokia N900 mobile handsets (see Figure 4) running Maemo operating system. The handset in the measurements as a user-worn device, but basically any other worn microphone can be used. A N900 and its user form the node to be self-localized. The user carries his/her handset at the chest level approximately 20 cm from mouth (see Figure 5). Each node records the audio using its microphone. The sampling rate is 48000 Hz and bit depth is 16 bits.

5.4. Data preprocessing

The recorded audio collected by each N900 can be completely out of sync that is the time delays between the data streams can be several seconds. If so, the data streams have to be aligned to certain extent. NB: this is a practical issue and the proposed self-localization system does not require sample-accurate synchronization between data streams.

The collected data contains a lot of frames with silence or noise and reverberation corrupt speech. This results in outliers in TDOA estimates, which is the primary input to the proposed system. Therefore, simple sequential filtering of TDOA estimates was used. The data alignment and outlier are performed using the methods presented in [10].

5.5. Image Based Reference Node Positioning System

To evaluate the performance of the method, reference coordinates of the nodes need to be acquired. This is performed using four video cameras installed in the room.
Figure 5: Four views into the room. In each measurement, cameras captured the recording to enable the determination of ground truth node positions.

Figure 6: The measurement plan for node 3 movement and actual track. The planned node 3 route is node 3-node 4-node 2-node 4. The planned path is illustrated in panel a with green line. A two-dimensional projection of the three-dimensional coordinates is illustrated on panel b. The three-dimensional coordinates are derived from annotated pixels that converted into room coordinates using the transformation presented in Section 5.5. Panel c presents which node is emitting at given time in Recording 3.

From four different viewpoints into the room, it is possible to estimate the 3D coordinates of the targets i.e. nodes visible in all four views. The detailed explanation of obtaining reference coordinates can be found in Appendix A.

6. Real-Data Evaluation

The evaluation of the proposed self-localization system is made by comparing the acoustically estimated coordinates to the image based reference coordinates. The self-localization coordinate system is subject to transformation in E(3), and is thus different from the room coordinate system. Furthermore, the estimates are calculated independently in sequential frames. Therefore, the estimated coordinates need to be aligned to the room coordinate system in each frame independently in order to compare them to the reference coordinates (see Section 5.5). A linear transformation that maps the relative coordinates \( \hat{O} \) to reference coordinates can be written as

\[
O = R\hat{O} + b^T,
\]

where \( R \) is rotation and reflection matrix. \( b \) is vector of ones and \( b \) translation vector i.e. the translation is the same for all the nodes. The Procrustes analysis can be used to estimation the alignment transformation (see e.g. [15, Chapter 19]). Since Procrustes performs minimization task in estimating \( R \) and \( b \), there is some estimation error between \( O \) and the physical coordinates. It is noted that the Procrustes analysis involves estimation of scaling would make the evaluation ignore the fact that the estimated object positions are given in meters. However, it is possible to perform the Procrustes analysis by estimating only \( R \) and \( b \).

The results are calculated as Root Mean Square (RMS) error over each recording for each node. That is,

\[
E_i = \frac{1}{T} \sum_{t=1}^{T} \epsilon_i(t),
\]

where \( \epsilon_i(t) = ||(\alpha_i(t) - \hat{\alpha}_i(t))|| \).

7. Drift Analysis

The purpose of drift analysis is to find out whether the used equipment i.e. N900s have significant clock drift that should be taken into account in the proposed self-localization algorithm. The drift analysis is performed using Sennheiser MKE 2 microphone, which is connected to a RME Fireface 800 analog-to-digital converter and the resulting signal is the reference. MKE 2 is attached right next to the microphone of an N900.

In order to evaluate the amount clock drift of the used hardware, first the audio streams have to be roughly aligned since their time axis origin may differ by several seconds. After the rough alignment, sample accurate alignment can be performed.

Let \( x(t) \) and \( y(t) \) denote the signals of equivalent microphones at time \( t \). \( x(t) \) is the reference microphone, i.e., the signal that is captured according to reference clock. It is assumed that no gain or phase changes occur. A time offset of \( \Delta \) samples and offset change rate of \( \Delta \eta \) samples/second i.e. drift exists between clocks used to sample the signals. The relation between signals is written as:

Matlab function \texttt{procrustes} [37] is used and scaling is omitted by setting \texttt{scaling} to \texttt{false}.
to estimate $\eta$, it is divided into two parts $\eta_r$ and $\eta_f$. $\eta_r$ is rough offset between signals and it is estimated utilizing energy envelopes of $x(t)$ and $y(t)$. $\eta_f$ is sample accurate offset, which is estimated using cross-correlation.

### 7.1. Sample Accurate Offset Estimation

Align signals at frame level using energy envelopes first, then cross-correlation is used to estimate the offset between the signals. The cross correlation in the $l$th analysis block is written as

$$r(\eta, l) = \sum_{t=0}^{L-1} x((L + t)l) y((L - \eta_r + t + \eta)),$$

where $L$ is the analysis window length, which is here set to 16384 samples. $\eta_r$ is the rough offset estimate in samples obtained from analyzing energy envelopes. The function $r(\eta, l)$ has a peak on time axis corresponding the time offset in the $l$th frame and is estimated as:

$$\eta_f(l) = \arg\max_{\eta} r(\eta, l)$$

As a result $l_{max}$ (the number of frames) offset values $\eta_f(l)$ are obtained. Due to rough alignment, it is known that $\eta_f(l) \in [-T, T]$ i.e. sample accurate offset estimate cannot be less or exceed the rough alignment block length $T$. Therefore such estimator is regarded as outlier.

The final alignment is obtained by combining the rough offset estimate and sample accurate offset:

$$\eta(l) = \eta_r + \eta_f(l), \forall l$$

### 7.2. Clock Drift

In case there is zero clock drift i.e. $\Delta \eta(l) = 0, \forall l$ and $\eta(l)$ is constant over a recording. To estimate the drift, the offset estimate time series are investigated. Figure 7 presents the offset values estimated over one of the recordings used to evaluate the proposed self-localization system. Clearly, the drift is almost linear over the recording. To estimate the drift, a line is fit to the data and resulting function is

$$f(t) = \eta_c + \Delta \eta_c t,$$

where $\eta_c$ is constant representing the offset in the beginning of the recording and $\Delta \eta_c$ is the drift. Matlab function polyfit is used to estimate $\eta_c$ and $\Delta \eta_c$. In the recording presented in Figure 7 the offset $\eta_c \approx 34986$ samples and the drift $\Delta \eta_c \approx 0.24743$ samples in a second. The drift is approximately the same in all recordings.

The analysis window for self-localization system is 0.1707 s (8192 samples). We conclude that no significant drift occurs during a single analysis window that would require its acknowledgement in the proposed self-localization system with the used equipment.

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**Figure 7: Drift analysis.** The offset values estimated over the whole recording show a linear drift in N900 clock. The drift is estimated by fitting a line on the data using Matlab function polyfit.

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### 8. Results

This section presents the performance of the proposed self-localization system. The performance is evaluated using five approximately two-minute real data recordings. In each recording, there are four nodes to be self-localized. The real data measurements are explained in detail in Section 5. Figure 8 and Table 1 present the results.

In Figure 8 RMS error is presented over the duration of the recordings 1–5. Each line presents the mean RMS of the four nodes (21). For instance, at 80 s from the beginning of Recording 1 the average RMS error is approximately 250 mm.

The calibration phase can be seen in Figure 8 approximately from 0 to 25 seconds. The self-localization RMS error in non-moving scenario is below 100 mm in all the recordings which agrees with the previous findings [10][11].

The dynamic phase, that is, two nodes are moving, starts in each recording approximately at 25 seconds from the beginning of the recording. The change from the non-moving phase to the dynamic can be seen in larger variation of RMS error compared to non-moving scenario. The estimation of the coordinates is conducted from pairwise distances and therefore the behavior of the error is coherent in all nodes’ coordinate estimates. In the dynamic scenario, error varies between 25 mm and 275 mm in the recordings, and the average error over all recordings is between 68 mm and 110 mm as shown in Table 1, which summarizes the results of Figure 8. The RMS error is the average over the recording for each node. The bottom row is the mean RMS error over all nodes for each recording. It can be seen that the proposed self-localization system achieves an average RMS error of approximately 100 mm.
Table 1: RMS Error in millimeters.

<table>
<thead>
<tr>
<th>Recording</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Node 1</td>
<td>74</td>
<td>68</td>
<td>79</td>
<td>75</td>
<td>81</td>
</tr>
<tr>
<td>Node 2</td>
<td>83</td>
<td>92</td>
<td>80</td>
<td>78</td>
<td>82</td>
</tr>
<tr>
<td>Node 3</td>
<td>82</td>
<td>104</td>
<td>90</td>
<td>102</td>
<td>85</td>
</tr>
<tr>
<td>Node 4</td>
<td>110</td>
<td>99</td>
<td>92</td>
<td>83</td>
<td>72</td>
</tr>
<tr>
<td>Mean over all nodes</td>
<td>87</td>
<td>91</td>
<td>85</td>
<td>85</td>
<td>80</td>
</tr>
</tbody>
</table>

Figure 8: RMS error of the proposed self-localization system in five real data recordings.

Figure 8 shows the RMS error of the proposed self-localization system in five real data recordings.

9. Discussion

As illustrated by Figure 8, the RMS error during the calibration phase is smaller and approximately constant compared to dynamic scenario. The larger error during the dynamic phase may result from several reasons, which include motion model, filtering parameters, and annotation inaccuracies. Related to motion model, the Kalman filter parameters were selected by hand to minimize the error with the test set. The Kalman filter parameters are $\Delta t = 1$, $Q = 0.2$, and $R = 0.02$. An automated parameter selection could result in smaller error. However, it is expected that gains by parameter refinement are small, since a moving source emits only sequentially, during silent periods the tracking uses only the prediction step of the Kalman filter. The reference room coordinates are obtained by manual annotation of the recordings. Therefore, some amount of error is explained by the used annotation method. For instance, choosing exactly the intended annotation point in each frame is impossible due to large number of image frames (approximately 1500 per camera in each recording). Furthermore, the annotation point is not always visible for all four cameras. In such a case, the annotation was made by best guess.

In summary, RMS error of the presented self-localization is sufficient for many applications e.g. continuous localization of the nodes. For microphone array calibration purposes the error may be too high.

The proposed system targets self-localization in dynamic scenario (moving nodes). However, the system would operate normally if nodes are non-moving. This scenario corresponds to calibration phase (see Section 5.1).

Often in case of ad hoc acoustic sensor networks the nodes are unsynchronized, i.e., temporal offsets between nodes may differ significantly and the proposed system is designed to take into account the time differences. However, the system would operate normally with synchronized nodes. In (4) this would correspond to having pairwise temporal offsets $\alpha_{ij} = 0$.

The proposed system uses TDOA for self-localization, therefore the performance is directly affected by the quality of TDOA. If the target audio segments (here speech) are short, in some environment there may not be valid TDOA estimates (i.e. direct path sound) for the proposed system to obtain correct node positions. Furthermore, the proposed system is designed to operate on speech signal\(^7\). Other signal type may require different parameters e.g. in TDOA estimation.

Finally, let us review the advantages of the proposed method. After the calibration phase, an alternative self-localization method could be to use non-moving nodes to localize the moving ones and to estimate node geometry. Such a system would alternate which node positions are fixed and which are updated. However, this approach suffers from error accumulation, since the node positions are reused. In contrast to this approach, our method fundamentally tracks pairwise distances between the nodes in a low-dimensional space $(N - 1)$. In this approach there is no feedback of positioning error. Furthermore, the proposed method is capable of self-localizing in a situation where every node is moving. The alternating approach requires at least four static nodes to perform 3D localization.

10. Conclusion

The article presented an acoustic self-localization system that solves the self-localization problem of moving independent nodes based on speech emitted by users wearing devices that contain a microphone. Compared to earlier acoustic self-localization systems such as [10],[11], the proposed system is the first to the authors’ knowledge that allows the node movement and simultaneous self-localization. The general self-localization problem consists

\(^7\)Speech content is Harvard sentences [38].
of solving the positions of microphone and sound sources, and temporal offsets of the microphones [12],[39]. The presented system focuses on determining the node locations, but it takes the temporal offsets into account in its design. The presented system achieves an accuracy of approximately 10 cm for moving sound sources.

**Appendix A. Image Based Reference Node Positioning System**

To evaluate the performance of the method, reference coordinates of the nodes need to be acquired. Since nodes are moving, the task is not straightforward. This is performed using four video cameras installed in the room. The fundamental idea is to annotate each node position frame-by-frame in each video camera stream and transform the annotated pixel coordinates into 3D physical room coordinates using a learned projection matrix.

The method to obtain the reference coordinates has its background in 3D model scene reconstruction and camera calibration using multiple views [40]. Let us consider $C$ cameras and $P$ physical 3D Cartesian locations $o_p = [o_p^x, o_p^y, o_p^z, 1]^T$, where $p = 1, \ldots, P$. The projection matrix can be formulated as

$$
\begin{align*}
\mathbf{u}_p &= W^c o_p, \\
\mathbf{u}_p' &= [u_p^x, u_p^y, u_p^z, 1]^T
\end{align*}
$$

(A.1)

defines the mapping between physical coordinates $o_p$ and pixel coordinates $\mathbf{u}_p' = [u_p^x, u_p^y, u_p^z, 1]^T$ for camera $c = 1, \ldots, C$. The projection $W^c$ is a $3C \times 4$ matrix [40] [41].

In a multiview setup, the corresponding projection can be formulated by concatenating pixel coordinates from all $C$ cameras into a matrix $U$ as follows:

$$
\begin{bmatrix}
\mathbf{u}_1' \\
\vdots \\
\mathbf{u}_C'
\end{bmatrix}
= \begin{bmatrix}
\mathbf{W}^1 \\
\vdots \\
\mathbf{W}^C
\end{bmatrix}
\begin{bmatrix}
o_1 \\
\vdots \\
o_P
\end{bmatrix}
$$

(A.2)

where $W \in \mathbb{R}^{3C \times 4}$ and $O \in \mathbb{R}^{4 \times P}$ [41].

The problem is to find a transformation that maps the pixel coordinates to physical 3D coordinates. The mapping is formulated as

$$
\hat{O} = \Psi U,
$$

(A.3)

where $\Psi \in \mathbb{R}^{4 \times 3C}$, $\hat{O} = [\hat{o}_1, \ldots, \hat{o}_P]^T$ are the estimated 3D locations $\hat{o}_p = [\hat{o}_p^x, \hat{o}_p^y, \hat{o}_p^z, 1]^T$.

To estimate $\Psi$, a set of $P$ pixel coordinates from $C$ viewpoints is needed along corresponding $P$ 3D physical coordinates. To achieve good accuracy, $P = 54$ pixel coordinates corresponding 54 3D locations were extracted. Due to high number of points, an aluminum cross-shape construction was installed in the room (see Figure A.9). Each calibration point in each arm of the pole was marked using red tape. The purpose of the tape is to make the calibrations points visible for each camera. The distance between adjacent points in each arm is 10 cm. Two additional reference points outside the pole were measured. The reference points are illustrated from Camera 1 viewpoint and some of them are highlighted with arrows in Figure A.9.

The locations of the reference points in room 3D coordinates were determined using the knowledge of the pole location and the marker 10 cm interval information. The physical locations were determined using Leica DistoTM classic5a [42] laser distance measurement tool by measuring each coordinate separately with respect to the origin in the room.

Next, the corresponding pixel coordinates were extracted from the four cameras. The 800 x 600 pixel (RGB) images captured by the camera were marked by a human annotator all calibration pixel locations in all cameras. Identical consumer-level Logitech C905 [43] cameras were used.

There are many ways to find mapping $\Psi : U \rightarrow \hat{O}$. A straightforward way to estimate $\Psi$ is finding the inverse matrix of $U$ and thus $\Psi = O^T U^{-1}$, where $U^{-1}$ is the inverse matrix of $U$. However, the $U$ is a nonsquare matrix and therefore it has no inverse matrix. We can estimate Moore-Penrose pseudoinverse of $U$. That is, $U^+ = U^T (UU^T)^{-1}$. Using the pseudo-inverse, the transformation is

$$
\hat{\Psi}_{LS} = \hat{O} U^+.
$$

(A.4)

where $\hat{\Psi}_{LS}$ is the least squares (LS) estimator of $\Psi$. The LS estimator is sensitive to outliers. Therefore, also more robust estimators such as Multivariate Least Trimmed Squares (MLTS)[44] and Partial Least Squares Regression (PLSR) estimator were tested. The conversion $\hat{\Psi}$ was tested by selecting test pixel coordinates from the cameras and measuring corresponding 3D locations in the room. The extraction of test pixel coordinates was done by installing a small but visible to the camera object on top of a stand at measured room coordinates and then choosing the pixel from each camera.

Finally, the accuracy of the estimator $\hat{\Psi}_{LS}$, $\hat{\Psi}_{MLTS}$ and $\hat{\Psi}_{PLSR}$ was determined using

$$
E_\Phi = \frac{1}{P} \sum_{i=1}^{P} e_i,
$$

(A.5)

where $e_i = ||o_i - \hat{o}_i||$. The PLSR estimator achieved the lowest $E_\Phi$ of 105 mm and thus $\hat{\Psi}_{PLSR}$ transformation was chosen for creating the 3D reference data. It is noted that the $\hat{\Psi}_{PLSR}$ may be a suboptimal estimator, but is sufficient for evaluation purposes. Testing different estimators is non-trivial and is left for later work.

Using camera calibration before estimating $\Psi$ did not lead to lower error of test points, and was therefore omitted.

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8Accuracy ±1.5mm [42].

9Matlab Toolbox [45] was used.
in the figure) were used to test the accuracy of the transformation. Additional measurement points near the pole (not illustrated in the figure) were used to test the accuracy of the transformation. There are a total of 54 calibration points. Green arrows are highlighted by the red arrows outside the calibration pole. There are also used to increase the accuracy of the transformation. Figure A.9: The pole with calibration marks. The calibration points are highlighted by the red arrows. Two points highlighted by two green arrows outside the calibration pole are also used to increase the accuracy of the transformation.

References


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