Theoretical Computer Science 453 (2012) 98–109

Contents lists available at SciVerse ScienceDirect

Theoretical Computer Science

journal homepage: www.elsevier.com/locate/tcs

Self-Localization based on Ambient Signals

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ARTICLE INFO

Keywords:
TDOA
Localization
Synchronization

ABSTRACT

We present an approach for the localization of passive nodes in a communication network using ambient radio or sound signals. In our settings, the communication nodes have unknown positions. They do not emit signals for localization and exchange only the time points when environmental signals are received: the time differences of arrival (TDOA). The signals occur at distant but unknown positions and they can be distinguished. Since no anchors are available, the goal is to determine the relative positions of all communication nodes and the environmental signals.

Our novel approach, the Ellipsoid TDOA method, introduces a closed form solution assuming that the signals originate from remote distances. The TDOA measurements characterize an ellipse from which the distances and angles between three network nodes can be inferred. In contrast to existing approaches, we do not require the receiver nodes to be synchronized. Furthermore, we can calculate the time offsets of the receiver clocks as a result of our calculations and synchronize the receivers in this way.

The approach is tested in numerous simulations and in indoor and outdoor settings, where the relative positions of mobile devices are determined using only the sounds produced by assistants with noisemakers.

1. Introduction

The increasing mobility of computing devices like smartphones, PDAs, laptops, and tablet computers is a motivation to revisit the localization problem from a fresh perspective. The usual approach is to include special hardware like GPS receivers, which adds extra monetary cost and power consumption. However, in shielded areas and for small distances, such location hardware cannot solve the problem. This is in particular the case for sensor networks in houses or tunnels. Then, the standard approach is to use anchor points in the communication network and calculate the positions by the time of arrival (TOA), time difference of arrival (TDOA) or by the received signal strength indication (RSSI) of radio signals. However, a stationary positioning infrastructure involves additional costs and requires precise calibration. So the next step is to omit any pre-calibrated infrastructure and determine relative positions of arbitrarily located devices.

Our approach starts with the following idea. Suppose we have a number of devices with microphones in a room which are connected by a communication network, e.g. mobile phones or laptop computers. Now, somebody walks through the room snapping fingers. Solely based on the time when these sound signals are received, all distances and angles between the network nodes are computed.

The direction and the distance of the finger snaps are initially unknown. We only assume that the finger snaps originate from far away. As this is not a realistic setting in most cases, our calculations yield only an approximation — though our

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0304-3975/$ – see front matter
doi:10.1016/j.tcs.2011.11.024

experiments point out that we obtain reliable results when the distances of the signal origins are at least as long as the longest edge between the receivers.

The practicability of this approach can easily be seen. Since most modern computing devices like laptops and smartphones are equipped with everything we need (microphone, wireless LAN) the software can be run without any cost or effort. Sound sources are widely available in crowded areas like market places or in an open air concert. The noises of the people might already be sufficient to be localized.

Or consider localization in a wireless sensor network which has been a time consuming task. Our scheme enables the experimenter to automatize positioning of sensor nodes equipped with microphones just by producing some sharp sound signals before or after a field test to determine the locations of the sensors.

In our contribution we enhance previous approaches in that we do not require the receiver devices to be synchronized. The need to synchronize devices has been a serious limitation as synchronization is costly in terms of network communication, and in mobile communication networks like GSM or UMTS clock synchronization is even a challenging task because of the unreliability and the asynchronous bandwidth characteristics of these networks. Furthermore, as a result of our calculations we yield the time offset between all pairs of receivers and we can in this way synchronize the receivers using only the signals from the environment. Our approach could be used to support synchronized algorithms in wireless sensor networks, for example time slot methods and round based algorithms.

Our software might be extended to use with radio signals instead of sound signals. This will require special hardware to detect time points of radio signals which have to be more precise due to the speed of light. Given such hardware it is possible to compute the relative positions of network nodes like notebook computers, mobile phones, tablet computers or PDAs by using ambient radio signals coming from Wi-Fi base stations, radio or TV broadcast, TV satellites or lightnings. Of course such a localization method must be combined with anchors which give absolute locations.

The special quality of our approach is that we do not have to know the positions of the signal sources. We compute them as well. As a consequence, we can make use of any signal for localization. Even encrypted GPS signals from an unknown positioned satellite or just the signal of a mobile phone of a by-passer will function as an information source. This clearly separates our approach from prevalent approaches which use the information of time of flight, i.e. time of arrival (TOA) or direction of arrival (DOA).

1.1. Related work

Localization with *known* receiver or sender positions has been a broad and intensive research topic with a variety of approaches. A popular application is GSM localization of mobile phones. Various techniques exist, including angle/direction of arrival (AOA/DOA), time of arrival (TOA, ''time of flight''), and time difference of arrival (TDOA) [1]. U-TDOA is a provider-side GSM multilateration technique that needs at least three synchronized base stations. As a client-side implementation needs special hardware, it is hardly prevalent in common mobile phones. Instead, many approaches introduce a distance function based on the received signal strength indication (RSSI). Stable results in the range of meters can be achieved by fingerprinting using a map of base stations [2].

Similar is localization using the RSSI function of Wi-Fi signals instead of GSM. Methods include Bayesian inference [3], semidefinite programming for convex constraint functions [4,5] a combination of Wi-Fi and ultrasound for TOA measurements like the Cricket system [6] or combinations of methods [7].

RSSI evaluation usually comes with difficulties for indoor localization due to the unpredictability of signal propagation [8]. We focus on TDOA analysis in our approach. For TDOA localization of sound and RF signals there is a basic scheme of four or more known sensors locating one signal source. It is solved in closed form [9,10] or with iterative methods [11]. TDOA calculation can be done by cross correlation of pairs of signals. An optimal shift between signals is calculated, corresponding to the angle of the signal [12,13]. However, we use signals with a characteristic peak.

Moses et al. [14] use DOA and TDOA information to solve the problem of *unknown* sender and receiver positions. Though sounding similar to our problem, both problem settings differ fundamentally. The additional DOA information enables the authors to apply some sort of ''bootstrapping'': Initial starting points can be found to solve the problem incrementally.

Localization of unknown receivers is demonstrated in [15], where notebook computers with onboard audio emitters are located by time of flight information. The location of mobile devices is calculated in [16], given some anchor points in space, where the RSSI of unknown Wi-Fi access points is used.

The calculation of unknown receiver positions using time differences of arrival, but no anchor points, uses synchronized receivers in most cases. An iterative approach for the general case is presented in [17]. In a special case of five receivers in space or four receivers in the plane the positions of the receivers can be calculated in closed form using matrix factorization [18].

When less than four receivers are available the equation system is underdefined and cannot be solved uniquely, which is described in [19]. Under the assumption of distant signals the positions of three receivers can be calculated using TDOA. An approach requiring synchronized receivers is presented in [20].

Synchronization is expensive in terms of network communication. For radio signals and their higher speed of light it does not seem likely to achieve precise synchronization at all. In our approach we calculate the receiver positions without the need to synchronize the devices.

1.2. Problem setting

Consider a communication network of n nodes $\mathbf{M}_1, \ldots, \mathbf{M}_n$, where $\mathbf{M}_i \in \mathbb{R}^2$ $(i = 1, \ldots, n)$ denotes the unknown position in two-dimensional Euclidean space. Now m sound (or radio) signals are produced at unknown time points $t_1, \ldots, t_m$ and at unknown locations $\mathbf{S}_1, \ldots, \mathbf{S}_m \in \mathbb{R}^2$. Each signal $\mathbf{S}_j$ $(j = 1, \ldots, m)$ arrives at receiver $\mathbf{M}_i$ at time $t_{i,j}$ which is the only input given in this problem setting. We can measure this time up to an error margin which we assume to be Gaussian distributed. We assume that the signals propagate in a straight line from the signal origins to the receivers with the constant signal speed c_s and that they are distinguishable.

The problem is to compute all the distances and angles between receivers, solely from the times when environmental signals are received. Of course then, the signal directions can be computed from this information. The mathematical constraints can be described using the signal velocity c_s, the time t_j of signal creation and the time $t_{i,j}$ when the signal is received at $\mathbf{M}_i$:

$$c_s\,(t_{i,j} - t_j) = \|\mathbf{M}_i - \mathbf{S}_j\| \tag{1}$$

where $\|\cdot\|$ denotes the Euclidean distance in two-dimensional space.

By squaring the equations of form (1) we yield a quadratic equation system which can be written in quadratic form. Depending on the number of signals and receivers this system is under-defined, well-defined or even over-defined. It can be rewritten as an optimization problem where a polynomial function of degree four needs to be minimized. A common approach is to optimize parameters using iterative algorithms. They find a solution to the problem in many cases. However, efficient solutions to such problems in general remain an open question.

Our solution considers the case where the signal sources are so far from the nodes that the sound is received from the same angle at all nodes. Then, the time difference between two nodes depends only on the angle between the signal beam and the line between the two nodes.

In this contribution we present a closed form solution for three nodes in two-dimensional space — the *Ellipsoid TDOA method*. We have tested our approach in numerical simulations of sound sources with realistic distributions of Gaussian error.

Later on, we show how our algorithm performs in real-world indoor and outdoor experiments. In these experiments we have generated series of signals at random positions on circles around the computers by clanking a bottle or two wooden planks. This is the sole information we need to compute the relative distances of the computers.

2. Ellipsoid TDOA method for distant sources

Our novel approach, the Ellipsoid TDOA method, calculates the distances $d_1 := \overline{AB}$ and $d_2 := \overline{AC}$ and the angle $\alpha := \angle_{CAB}$ between three nodes A, B, and C in a triangle in the plane, see Fig. 1. The triangle, which is hereby uniquely defined, can be of arbitrary shape. The nodes can even be collinear. However, any two nodes must not reside at the same spot. This singularity can be detected and sorted out. At the same time we obtain the time offset between any pair of two receivers, in this way we can use our approach to synchronize the receivers.

As the only source of information we use the time difference of arrival of at least five signals from different locations. The signals characterize an ellipse, as we describe in the following section, which uniquely defines the triangle ABC. We do not know the origins of the signals, we only assume that they are far away from the nodes. In case the receiver clocks are synchronized the minimum number of required signals is reduced to three.

2.1. Receiver triangle

For three receivers A, B, C in the plane and a distant signal source $\mathbf{S}_j$ the discrete signal is received by the receivers at time points $t_{A,j}$, $t_{B,j}$ and $t_{C,j}$. For clarity we omit the signal index j for the rest of this section. Define

$$\Delta t_1 = t_B - t_A \tag{2}$$

$$\Delta t_2 = t_C - t_A \tag{3}$$

where Δt_1 and Δt_2 are the time differences of arrival (TDOA) between A and B, respectively A and C. For $\alpha = \angle_{CAB}$ and using the assumption of infinite distant signal origins we state:

$$x := \Delta t_1 = d_1 \cos(\gamma - \alpha/2) \tag{4}$$

$$y := \Delta t_2 = d_2 \cos(\gamma + \alpha/2) \tag{5}$$

where γ denotes the direction of $\mathbf{S}$ with respect to the bisection of α. Combining the equations we derive the following ellipse equation:

$$x^2 \frac{1}{d_1^2} + y^2 \frac{1}{d_2^2} + xy \frac{-2\cos\alpha}{d_1 d_2} = \underbrace{\frac{1}{2} - \frac{1}{2}\cos 2\alpha}_{\sin^2\alpha} . \tag{6}$$

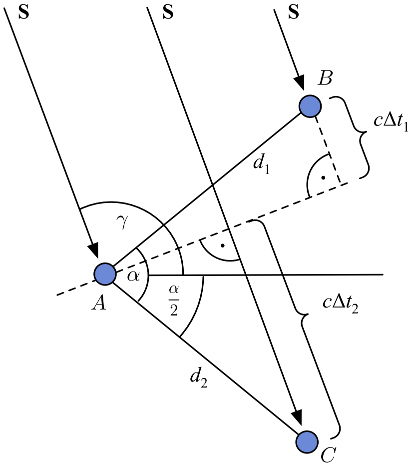

Fig. 1. Three receivers A, B, C and a signal on the horizon with direction **S**.

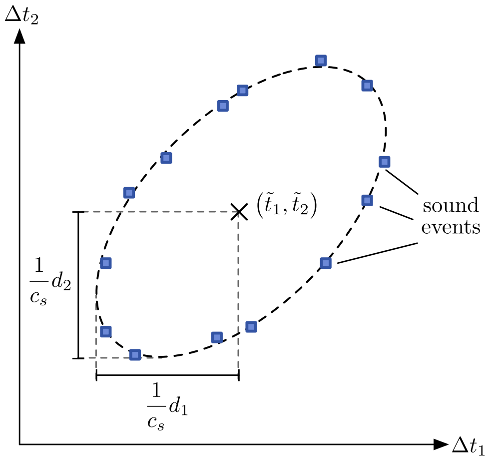

Fig. 2. Multiple distant sound signals with time difference pairs $(\Delta t_1, \Delta t_2)$ in two dimensions form an ellipse.

Normalization by division by $\sin^2 \alpha$ (under the assumption $\alpha \notin \{0, \pi\}$, i.e. A, B, C are collinear) leads to the ellipse parameters

$$a = \frac{1}{d_1^2 \sin^2 \alpha}, \qquad b = \frac{1}{d_2^2 \sin^2 \alpha}, \qquad c = \frac{-2\cos\alpha}{d_1 d_2 \sin^2 \alpha}$$

for $ax^2 + by^2 + cxy = 1$.

Ellipsoid TDOA localization requires at least three pairs of time differences $(\Delta t_1, \Delta t_2)$ from different distant signal origins. From these points we compute the ellipse equation with parameters a, b, c, see Fig. 2. Then, we use the above equations to compute d_1, d_2 and α which can be done by the following equations:

$$d_1 = 2\sqrt{\frac{b}{4ab - c^2}}, \qquad d_2 = 2\sqrt{\frac{a}{4ab - c^2}}, \qquad \alpha = \arccos \frac{-c}{2\sqrt{ab}}. \tag{7}$$

2.2. Linear regression

Synchronized receivers. Three ambient signals are sufficient to find the ellipse for two dimensions if the receivers are synchronized. Since ambient radio or sound signals are no scarce resource additional signals can be used to overcome the inaccuracies caused by imprecise time measurements and other error sources. In this way a higher number of signals increases the robustness of the calculation. Given a sufficient number of $m \geq 3$ signal sources that form a set of (x, y)-tuples we obtain a system of linear equations

$$ax_j^2 + by_j^2 + cx_j y_j = 1 \tag{8}$$

where $1 \leq j \leq m$. We use linear regression to reconstruct the parameters of this ellipse. In matrix notation this is:

$$\underbrace{\begin{pmatrix} x_1^2 & y_1^2 & x_1 y_1 \\ \vdots & \vdots & \vdots \\ x_m^2 & y_m^2 & x_m y_m \end{pmatrix}}_{\mathbf{Q}} \underbrace{\begin{pmatrix} a \\ b \\ c \end{pmatrix}}_{\mathbf{u}} = \mathbf{1}.$$

If $m > 3$ we use the least squares method and solve for the ellipse parameters:

$$\left(\mathbf{Q}^T\mathbf{Q}\right)\mathbf{u} = \mathbf{Q}^T\mathbf{1} \quad \Rightarrow \quad \mathbf{u} = \left(\mathbf{Q}^T\mathbf{Q}\right)^{-1}\left(\mathbf{Q}^T\mathbf{1}\right). \tag{9}$$

If $m = 3$ we solve $\mathbf{u} = \mathbf{Q}^{-1}\mathbf{1}$. For $m < 3$ the system is under-determined and cannot be solved uniquely. We use the Eq. (7) of the previous subsection to compute the geometry of the triangle ABC with the parameters a, b and c.

Unsynchronized receivers. If the receivers are not synchronized we yield a constant offset of the time differences between pairs of receivers. Then, the center of the ellipse is shifted. The ellipse equation

$$ax_j^2 + by_j^2 + cx_jy_j + dx_j + ey_j = 1 \tag{10}$$

describes an ellipse in general configuration, which is in matrix notation:

$$\underbrace{\begin{pmatrix} x_1^2 & y_1^2 & x_1 y_1 & x_1 & y_1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_m^2 & y_m^2 & x_m y_m & x_m & y_m \end{pmatrix}}_{\mathbf{Q}} \underbrace{\begin{pmatrix} a \\ b \\ c \\ d \\ e \end{pmatrix}}_{\mathbf{u}} = \mathbf{1}.$$

At least $m = 5$ signal sources are required to describe the shifted ellipse. We calculate the linear least squares regression as in the synchronized case using Eq. (9) and solve for $\mathbf{u} = (a, b, c, d, e)^T$. We convert the parameters of this ellipse to translation invariant coefficients a', b', c' describing the shape of the ellipse by

$$a' = a\frac{K}{L}, \qquad b' = b\frac{K}{L}, \qquad c' = c\frac{K}{L}, \quad \text{where}$$
$$K := 4ab - c^2 \quad \text{and} \quad L := ae^2 + bd^2 - c^2 + 4ab - cde, \quad \text{if } L \neq 0.$$

The conversion equations follow from the alternative ellipse representation

$$a'(x_j - d')^2 + b'(y_j - e')^2 + c(x_j - d')(y_j - e') = 1 \tag{11}$$

where d' and e' describe the translation of the center of the ellipse. Again we use the Eq. (7) to compute the triangle ABC by inserting the parameters a', b', c'. Additionally, we can calculate the synchronization offsets between the receivers A and B as $\tilde{t}_1 := d' = -(2bd - ce)\frac{1}{K}$ and between A and C as $\tilde{t}_2 := e' = -(2ae - cd)\frac{1}{K}$, if $K \neq 0$. Once the receiver triangle ABC has been reconstructed we can determine the direction of the signal origins from the triangle using multilateration, see [13].

To increase numerical stability we subtract the mean from the time differences before we perform the regression. This does not influence the results of the calculation, as a shift in the unknown offset time changes only the position and not the shape of the ellipse. Furthermore, we use LU decomposition to solve Eq. (9) instead of inverting the matrix $(\mathbf{Q}^T\mathbf{Q})$.

2.3. Covariance estimation

In some rare cases the regression result does not describe an ellipse. Then, we alternatively characterize the ellipse by calculating the mean and the covariance of the time difference measures.

Consider a distribution of m time differences $\mathbf{X} = \{\mathbf{x}_j\} = \{(x_j, y_j)^T\}$ that approximately describe an ellipse. The mean $\boldsymbol{\mu}$ and covariance Σ of the set of time differences are calculated by

$$\boldsymbol{\mu} = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} = \frac{1}{m}\sum_{j=1}^{m}\mathbf{x}_j, \qquad \Sigma = \begin{pmatrix} v_{11} & v_{12} \\ v_{21} & v_{22} \end{pmatrix} = \frac{1}{m}\sum_{j=1}^{m}(\mathbf{x}_j - \boldsymbol{\mu})(\mathbf{x}_j - \boldsymbol{\mu})^T.$$

The ellipse parameters are calculated by inverting the covariance matrix. We obtain the parameter vector $\hat{\mathbf{u}} := \frac{1}{|\Sigma|}\left(\frac{1}{2}v_{22}, \frac{1}{2}v_{11}, -v_{21}\right)$ describing the shape of the ellipse as in the previous section. The time offset between the receivers A and B and A and C is obtained from the mean of the time differences as $(\tilde{t}_1, \tilde{t}_2) := (\mu_1, \mu_2)$. In case the receivers are synchronized we set $\boldsymbol{\mu} = (0, 0)^T$.

Using variance estimation a solution can be found even if the three microphones are approximately on a line. However, the covariance ellipse, in contrast to the regression method, is susceptible to non-uniform distribution of the measurements, which leads to degradation of the approximation. We use the variance estimation as an alternative when we cannot find a solution using the regression method, for example when signals are close or when the receivers are collinear.

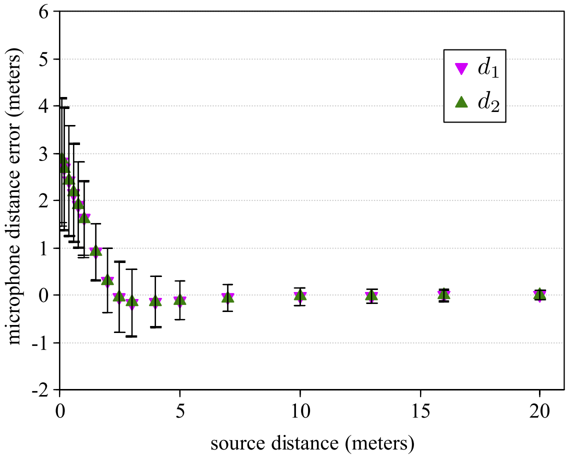

Fig. 3. Increasing sound signal distances above 5 m result in distance error means below 0.1 m and low standard deviation between experiment runs.

Since the assumption of infinitely far senders is not realistic the Ellipsoid method results in an approximative solution of the problem. The quality of the solution can be evaluated by calculating the residua of the regression or by calculating the Mahalanobis distance of every signal, given the covariance matrix Σ, which is $d_{2\Sigma}(\mathbf{x}_j, \boldsymbol{\mu}) := \sqrt{(\mathbf{x}_j - \boldsymbol{\mu})^T (2\Sigma)^{-1} (\mathbf{x}_j - \boldsymbol{\mu})} \to 1$ in case the measurement errors tend to zero.

The approximation is the best one can offer if only three receivers are available, since the problem for three general receiver positions is under-defined. If only two receivers are available we fall back to distance estimation techniques [21]. In the following we present simulations which indicate that the approximation behaves well if the signals are a small constant factor farer than the longest edge of the receiver triangle.

2.4. Simulation

We have tested the accuracy of this approximation algorithm with a computer algebra system. A simulation cycle consists of a number of sound sources arbitrarily arranged on a circle with a fixed radius around the origin. For every cycle three microphones A, B and C are randomized to arbitrary angles on a circle with a fixed radius of about 2.3 m. This allows for a large number of triangle configurations, in particular the triangles are not necessarily equal-sided or equilateral. In the equilateral case the triangle has an edge length of 4 m.

The m sound signals are received by the microphones at time points $t_{\mathbf{M},j}$ depending on the distance and the speed of sound. A probabilistic Gaussian error model is added to each timestamp to simulate measurement errors. For every device at location $\mathbf{M}$ a received timestamp is generated as

$$t_{\mathbf{M},j} = \tilde{t}_{\mathbf{M}} + t_j + \frac{1}{c_s}\|\mathbf{M} - \mathbf{S}_j\| + \epsilon_{\mathbf{M}}, \quad \text{where } j \in \{1, \ldots, m\},\ \mathbf{M} \in \{A, B, C\} \tag{12}$$

where $\tilde{t}_{\mathbf{M}}$ is the offset of the receiver's clock simulating synchronization bias, t_j is the send time of the signal, $\mathbf{S}_j$ is the location of the sender j and $\epsilon_{\mathbf{M}}$ is a Gaussian error variable.

For a set of different radii up to 20 m a series of 1000 tests with 12 sound signals is run. The calculated results d_1 and d_2 and the angle α between A and B are subtracted from the real values, which are read from the triangle properties.

In some cases the regression result does not describe an ellipse. This is especially the case when the assumption of distant signal origins is violated, i.e. the signals are close. Fig. 5 demonstrates an example of such a deformed ellipse as the result of nearby signals. Then, up to 25% of all regression attempts describe a hyperbola instead of an ellipse, which is also a solution to Eq. (8). To catch this case we use covariance estimation, which yields an adequate approximation of the ellipse. In this way we can even calculate a solution when the three microphones A, B and C reside close to a line. When the signals originate from a larger distance, which is the usual case, the ratio of hyperbolic regressions drops below 1%.

The results show a systematic under-estimation of the distances between microphones for short range signals which improves after the perimeter of the microphones has been left at about 5 m. Fig. 3 displays the mean error and standard deviation bars for d_1 and d_2. The angle errors show high standard deviation between the experiment runs within the perimeter of the microphones which stabilizes quickly upon leaving it, at a range of 5 m (Fig. 4). The diagrams represent the final approximation results, without a distinction if the regression method or the covariance estimation has been used.

A stress test was run to observe the behavior of the approximation in case of Gaussian signal runtime variances. For simplicity 12 distant sound signals are assumed (radius of 1000 m) and the Gaussian runtime error is increased up to a standard deviation of 2.0 ms. For comparison: In 1.0 ms a sound wave travels about 34 cm under normal conditions. Results show a slight over-estimation of the microphone distances and a moderate increase in the standard deviation of the angle error between runs. The ratio of hyperbolic regressions increases to about 8%. However, a Gaussian distributed error of

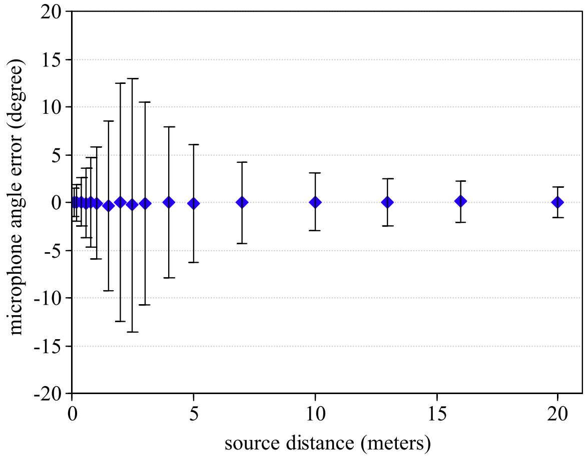

Fig. 4. Increasing sound signal distances above 5 m result in small angle approximation errors with a standard deviation below 5° between experiment runs.

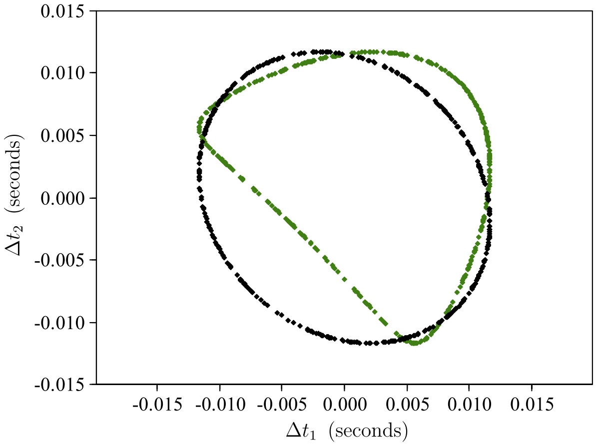

Fig. 5. The elliptical shape for distant signals (black) and a deformed shape when signals are near (green). In the latter case, the signals originate from a circle with radius 5 m.

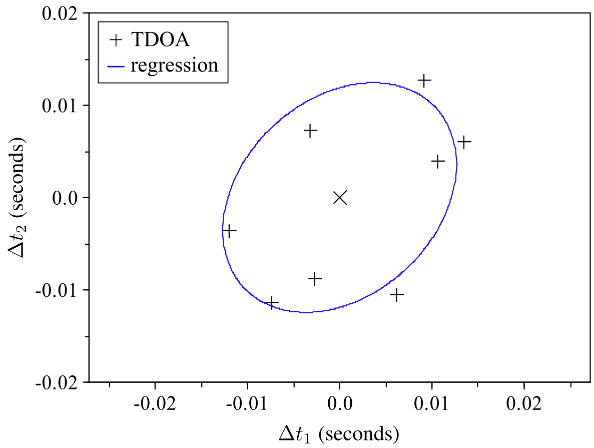

Fig. 6. Eight signals with Gaussian error of $\sigma = 2$ ms were received. The elliptical form is hardly recognizable because of the high error.

2 ms ranges inside the limits of nearly 3 m, which is a lot for a scenario with an edge length of 4 m. The time differences of this magnitude, drawn as x/y-plot, is hardly recognized as an ellipse any more (Fig. 6). In our real-world experiments we observed runtime errors with a standard deviation of about 0.2 ms, which is way below the errors we induced here. Also, the robustness of the algorithm can be improved by a higher number of sound signals.

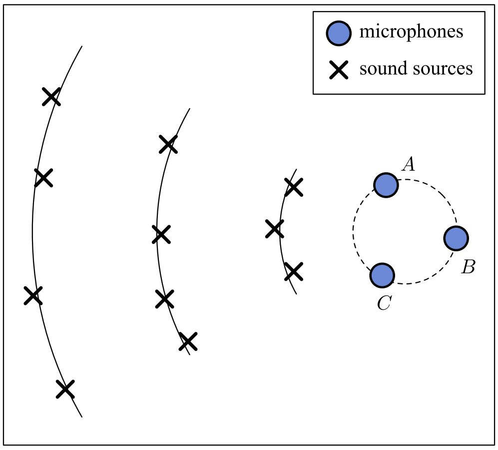

Fig. 7. Experiment setup in the lecture hall: series of random signals on concentric circles with varying radii around the computers.

3. Real-world experiments

We have tested this theoretical approach in several real-world experiments using a network of mobile devices and laptops as network nodes. We have presented this software framework in [21]. Our software establishes communication via a local area network (LAN) between several devices and establishes precise time synchronization. With the built-in microphones we record sound signals.

The audio track is searched for sharp sound events, like clapping or finger snapping and their points in time are determined. As a peculiar mark for a sound event we use the moment when the signal rises above an environment noise dependent threshold for the first time. Threshold comparisons showed to be the most reliable approach with only little drawbacks in precision. Maximum searches, either directly or derivative (edge detection) showed to be slightly more precise but prove to be ambiguous with fatal results in cases when hosts chose different maxima.

The detected signals are exchanged between the nodes using the communication network. With this information given each node can compute the relative locations using the algorithm described before.

3.1. Time synchronization

Unsynchronized TDOA localization has been done in distance estimation approaches and it is supported by the Ellipsoid TDOA method which we have presented in this contribution. However, in the following experiments we use synchronized devices because the minimum number of required sound events is reduced.

To get a global time reference the nodes elect a master based on priority IDs and synchronize to the master clock. The synchronization is achieved with a series of pings between the master and all other nodes to get a good estimation of the round trip time (RTT) to the master. The exchanged reference timestamps are filtered for high RTT (outliers), which results from network jitter, and corrected by 1/2 RTT, assuming the network packet took the same runtime in both directions.

Our experiments pointed out that clock drift correction is essential even with the utilized high precision event timer (HPET). Although running with accurately constant speed, drift rates between different clocks of 0.03% were observed, which is too high for our purposes, if untreated. Both time offset and clock drift between client and master are obtained by linear regression of the timestamp set. The precision we achieve is within 0.1 ms in a wireless LAN with an RTT of about 10 ms and within 0.01 ms in a wired LAN with an RTT of about 1 ms.

In our calculations we consider the offset between the receiver clocks while the drift of the clocks is ignored. The drift might be an issue when performing unsynchronized localization. However, in our experiments we observed that the drift of our hardware clocks is mostly static and does not change over time. So every clock has to be calibrated only once to eliminate the drift.

3.2. Experiments

The first real-world test was situated in a large lecture hall with a size of 17 m × 13 m at the University of Freiburg. We arranged 3 laptops *A*, *B*, and *C* in a small triangle residing on a circle of radius 2.3 m and connected them with an ethernet based LAN switch for communication. Note that the shape of the triangle of laptops can be arbitrarily chosen. The triangle was placed in a corner of the hall to test far distant sound sources up to 16 m. To examine the measurement results we noted down the positions of the laptop microphones with a precision of 2 cm and the sound sources with a precision of 10 cm. The distances between the laptops were $d_{AB} = 4.30$ m, $d_{AC} = 4.14$ m and $d_{BC} = 3.47$ m, which results in $\angle_{CAB} = 48.6°$.

In the experiment, we generated several sound events with an empty glass bottle and a spoon on concentric circles with varying radii around the laptop triangle (Fig. 7). The audio signals were recorded with the built-in microphones to detect

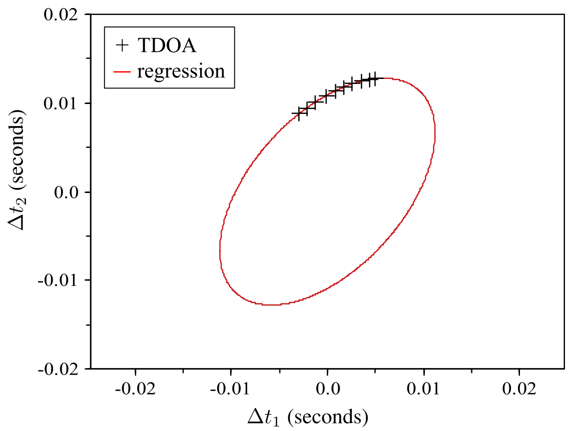

Fig. 8. Time differences from the approximation experiment as x/y-plot. Sound signals from a distance of 13 m arrive from only one direction.

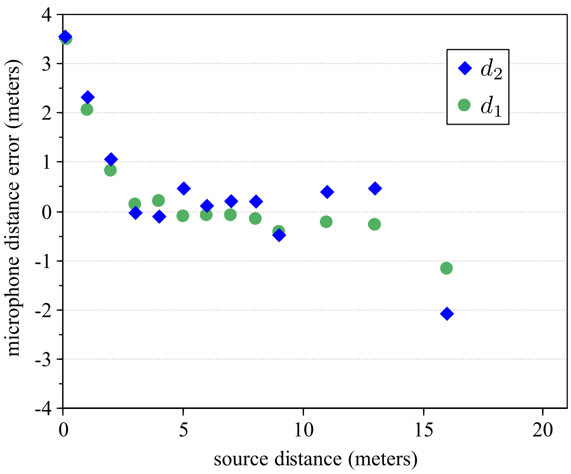

Fig. 9. Distance errors of d_1 and d_2 for the indoor experiment. Errors decrease quickly at a distance of 5 m except for one outlier at 16 m.

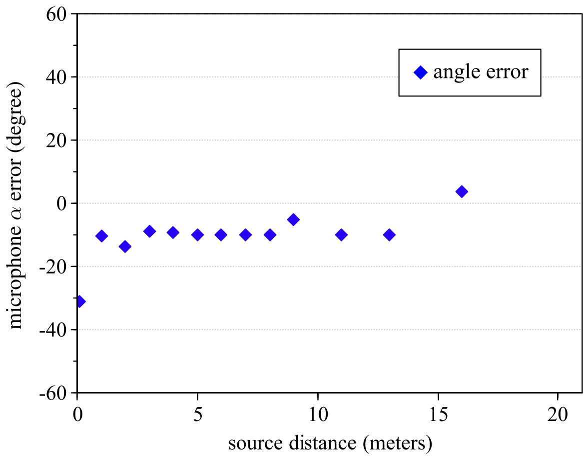

Fig. 10. Angle error of α for the indoor experiment. Angle errors decrease at a distance of 5 m except for a slight over-estimation of about 10°.

timestamps for the sound events. The Ellipsoid TDOA method was executed with the timestamps of a single radius as the only input to compute the distances between the microphones. Implausible sound signals with a time difference of more than 20 ms (corresponding to 6 m) were filtered.

The evaluation showed a good convergence of the microphone distance approximations d_1 and d_2 at circle radii of 4 m and above (Fig. 9). Errors fall below 0.5 m. Angle α resides at about 58°, which is an over-estimation of 10° (Fig. 10). With increasing sound signal distance results degrade, which we attribute to the narrowing sector of sound origins. Due to limited

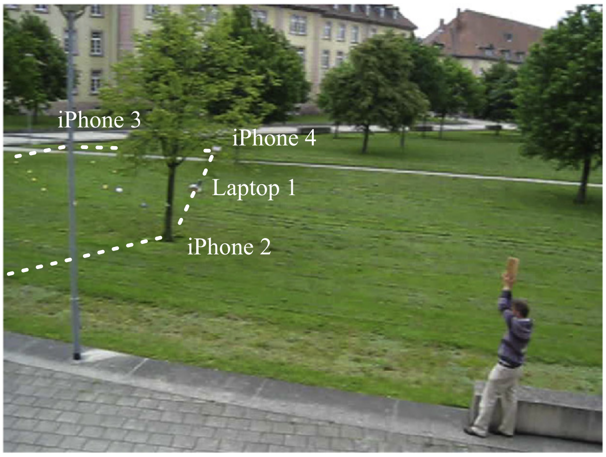

Fig. 11. Second outdoor experiment: Four iPhones and four laptops to be located from a series of distant sound signals. The experimenter in the picture claps the wooden planks.

room size they come from only one direction, thus making it harder to describe an ellipse (Fig. 8). This seems to be a drawback of the technique. Obviously we need signals from different angles to reconstruct the ellipse properly.

A second experiment was performed outdoors. We expected to find more realistic conditions like wind noise, birdsong, and the nearby rapid transit system. On the other hand there would be space to generate sound events from all directions, facilitating the ellipse regression. Eight nodes, consisting of four laptops and four Apple iPhones with our software running were placed randomly on a green area of the campus in an area of 30 m $\times$ 30 m. Their positions were measured precisely to within 20 cm. A Wi-Fi access point established communication between nodes for synchronization and for timestamp exchange.

A series of sound events was produced by an assistant circling the experiment perimeter in varying distances (see Fig. 11). He generated clearly audible sound signals by clapping two wooden planks. We obtained a series of 50 sounds of which none were filtered.

The Ellipsoid TDOA method was applied to any combination of three nodes which yields a total of $n(n-1)(n-2) = 336$ combinations. From every Ellipsoid method run the two distance measures d_1 and d_2 were obtained while angle α was discarded. Symmetric duplicates were removed, which resulted in 12 values for each of the 28 node pairs. The distance values belonging to the same node pair were averaged. They form a complete graph of node distances D_{ij}. By optimization we calculated the relative positions (x_i, y_i) of the microphones from the node distances in a rectangular coordinate system:

$$\arg\min_{x_i, y_i} \left(\sum_{i=1}^{n} \sum_{j=i+1}^{n} (x_i - x_j)^2 + (y_i - y_j)^2 - D_{ij}^2 \right).$$

The resulting point set was mapped to the real-world positions by a congruent rotation and translation. This was done by calculating the SVD (Singular Value Decomposition) of the point set correlation which provides an optimal transformation to minimize distances of associated points in the least squares sense.

The average distance from ground truth after mapping was 38 cm with a standard deviation of 14 cm. Fig. 12 shows the mapped point set and the real-world positions. Fig. 13 depicts the ellipse for the nodes *iPhone* 1, *Laptop* 1 and *Laptop* 4 as an example. For the distant sound signals the marks reside on the ellipse. Only when the assistant came closer to the microphones the infinite distance assumption was violated and the marks lie inside the ellipse. However, this did not affect the robust ellipse regression. Neither did the environmental noises affect our results, as they have no influence on the sound velocity and our signals were loud enough to predominate the noise.

Once the microphones have been located the positions of the sound sources can be obtained by hyperbolic multilateration. Or just the directions can be calculated using cosine equations, as described in [13].

4. Conclusions

Our considerations about the degrees of freedom point out that position reconstruction in the plane without any given anchors cannot be done with less than four receivers. However, the approximation scheme of remote signal origins enables us to state some propositions about the receiver positions and the direction of the signal sources even with three receivers.

We have developed the Ellipsoid TDOA method for position estimation of three passive receiver devices, which does not need any anchor points in space. We only need distinguishable sharp noise signals from distant origins and we assume that the sound of the signals propagates with constant speed on a direct line-of-sight to the receivers. Here, the signals are recorded and the time points of the signals are exchanged to the other devices using a communication network. Then, we can calculate the distances between three arbitrarily located receivers.

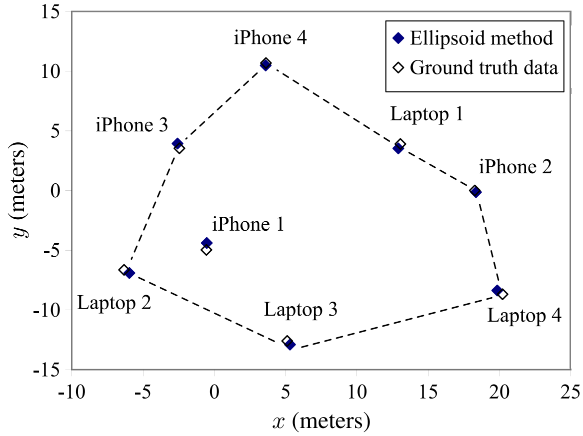

Fig. 12. Relative positions of the microphones mapped to the ground truth data in the second outdoor experiment. The average distance from ground truth is 38 cm (standard deviation: 14 cm).

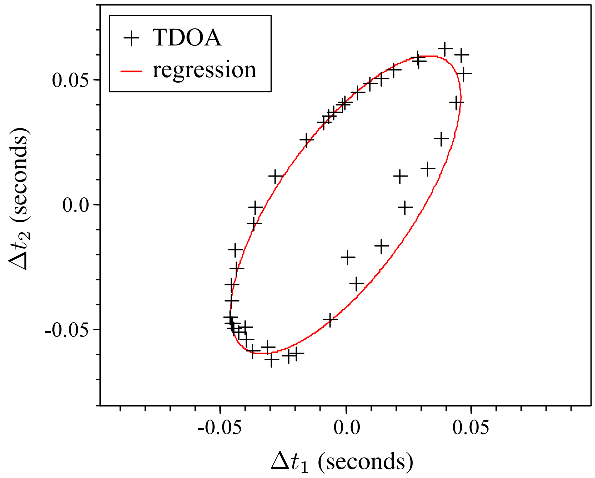

Fig. 13. Ellipse of time differences for the nodes *iPhone* 1, *Laptop* 1 and *Laptop* 4 of the second outdoor experiment. Nearby sound events deform the ellipse (*lower right sector*), instead of residing on the ellipse border.

The technique requires a minimum number of three signals in two-dimensional space if the receivers are synchronized. It directly benefits from an increased number of signal events. These are cheaply available in many environments. Then, our technique becomes very robust, even for noisy data.

Simulation and real-world tests suggest that our assumption of infinitely remote signal sources is not far-fetched. The parallax decreases quickly, as soon as we are outside the receiver perimeter. This allows us to use the approximation even in close-ranged scenarios.

Other than earlier approaches the Ellipsoid TDOA method can still be applied when the clocks of the receivers are not synchronized. Then the minimum number of signals increases to five. Additionally, we can use our approach to synchronize a network of communication devices as a result of our location calculations. This might be useful for field experiments with sensor nodes.

4.1. Future work

It is obvious that time synchronization is hard to achieve for radio signals due to the much higher speed of light. As the Ellipsoid TDOA method can be used without synchronization we can estimate distances between radio receivers using distant senders like Wi-Fi access points on a campus without the need to synchronize the clocks of the receivers, if we manage to timestamp radio signals sufficiently precise.

We have also seen some room for improvement in the approximation of the TDOA ellipse. In some cases of noisy data we found a slight, systematic over-estimation of receiver distances and angles. Visual analysis of the time differences showed that the resulting ellipse does not fit the corpus of the noisy data properly. This seems to be a result of deficient ellipse regression. While our regression minimizes the error "in some least squares sense", there are more sophisticated techniques available like *geometric fit* proposed by Gander et al. [22].

Furthermore, we plan to present an extension of the algorithm for three dimensions. Here, we calculate the distances between four receivers distributed in space. At least six signals are required if the receivers are synchronized and otherwise nine. From these signals we reconstruct an ellipsoid which describes the distances and angles and in this way uniquely defines the tetrahedron of receivers.

Further research will involve the use of non-discrete continuous signals, e.g. voices, traffic noise or analogous radio signals. By testing for best overlaps of such signals it should be possible to compute a time difference analogously to sharp signals. This would dramatically increase the information basis of the algorithm.

Acknowledgements

This work has partly been supported by the German Research Foundation (Deutsche Forschungsgemeinschaft, DFG) within the Research Training Group 1103 (Embedded Microsystems).

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