Estimation of 3D Device Position by Analyzing Ultrasonic Reflection Signals

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Abstract— **In future domestic *context aware* applications the location of mobile devices is often required. Ultrasound technology enables high resolution indoor position measurements. A disadvantage of state-of-the-art ultrasonic systems is that several base stations are required to estimate 3D position. Since fewer base stations would lead to lower cost and easier setup, a novel method is presented that requires just one base station. The method uses information from acoustic reflections in a room, and estimates 3D positions using an acoustic room-model. The method has been implemented, and verified within an empty room. It can be concluded that ultrasonic reflection data provides useful clues about the 3D position of a device.**

Keywords— **Location awareness, ultrasonic location systems, signal processing**

I. Introduction

In future computing systems and devices, *context awareness* will play an increasingly important role. A device or system that is context aware [4] makes use of information, that characterizes the context or physical situation that the device or its user is currently in. Often, the physical location of mobile devices is important context information. In such cases the term *location aware systems* can be used. For example, a user carrying a context-aware museum audio guide could be informed automatically about the exhibits at the current location.

Within the PHENOM project [14], several application scenarios were developed that bring location awareness into the area of domestic consumer electronics. The goal of location awareness in these applications can be functional, e.g. to improve the ease-of-use of consumer devices. But it may also enable new applications and experiences that are attractive to users. An example is the PHENOM portable screen for photo-browsing, that detects nearby displays, using them to display content.

Location-aware applications may need either absolute or relative location information. Some of our application scenarios require the absolute 3D position of devices within a room. The required position accuracy (typically ≤ 1 m) can not be delivered by wide-area systems like GPS. Therefore, a specialized indoor location system is required. Such systems exist [8] for several context-aware applications. These systems may use radio waves (RF), magnetic fields, ultrasonic waves, or combinations thereof. We focus on ultrasonic location systems, because of their proven track record in low cost accurate indoor position estimation.

Existing state-of-the-art ultrasonic location systems calculate a set of distances, using ultrasound time-of-flight measurements between fixed base stations (BSs) and a mobile device (MD). They subsequently use trilateration algorithms [8, 11] to calculate a 2D or 3D position of the MD. Existing systems are e.g. the Bat [1], Constellation and others from InterSense [7], Cricket [12], and the system by Randell and Muller [13]. A disadvantage of all these systems is that several units of infrastructure are required at fixed known positions in a room, e.g. attached to the ceiling. Generally four BSs are required in a non-collinear setup to estimate 3D position of MDs. In special cases like ceiling-mounted BSs, three is sufficient.

The required infrastructure and installation effort make these systems unsuitable for domestic deployment. Important requirements in the domestic domain are that a location system should be robust, safe, easy to install, minimal in its infrastructure, and low cost. These requirements led to our current research direction of a *single base station positioning system*. A single BS unit is the minimum of infrastructure (apart from no infrastructure at all), is easier to install than multiple units, and lowers system cost if BS units are mass-produced. Two methods were developed to realise such a single-BS system. The first method, presented in this paper, uses *ultrasonic reflections* in a room for estimation of 3D positions of devices. The second method [6] employs an acoustic array within the BS, that

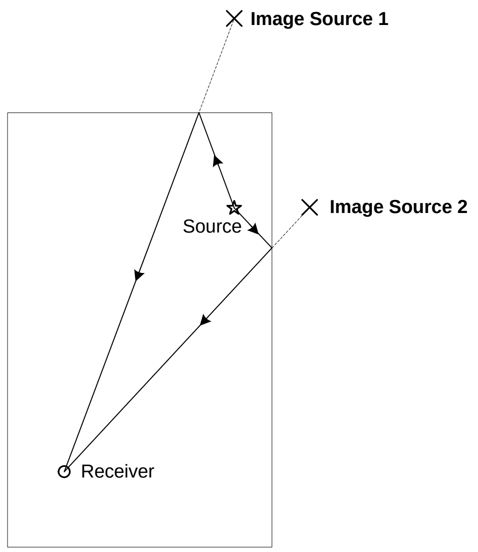

Fig. 1. Schematic 2D top view of a room, containing one acoustic source and one receiver. Two acoustic reflections (arrows) and associated image sources (crosses) are shown.

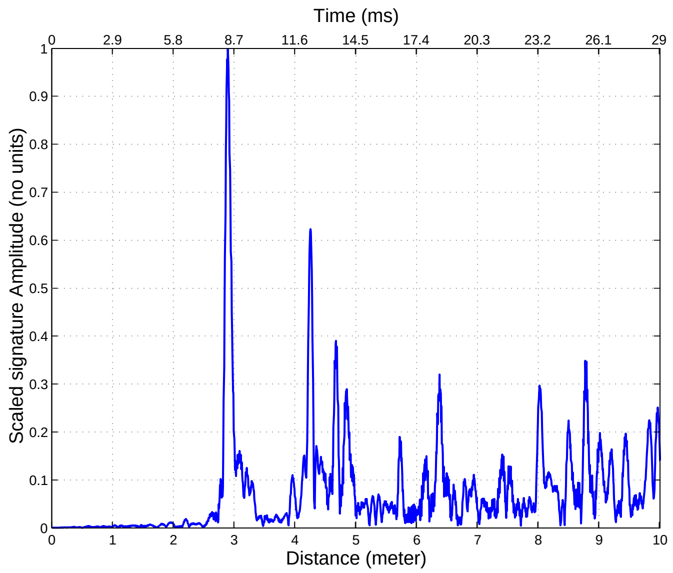

Fig. 2. Measured signature at position $\mathbf{x}_R = (2.60, 1.70, 1.27)$. The horizontal axes show time (top) and the corresponding distance interval of $[0, 10]$ m. (Signatures are obtained by the procedure in Section V-B.)

estimates both distance and direction of a MD, yielding a 3D position estimate.

II. Acoustical reflections in a room

In ultrasonic location systems, one or more transmitter units emit ultrasonic waves. For clarity it is assumed in this section that the fixed base stations (BSs) are transmitting, and mobile devices (MDs) are receiving. Transmitted ultrasonic waves propagate inside the room and cause reflections from surfaces such as walls, floor and ceiling. To clarify this, Fig. 1 shows a 2D top view of a room, with one acoustic source BS and one receiver. The source emits a direct sound wave towards the receiver along the line-of-sight (LOS) path, but sound also reflects off the four walls and arrives at the receiver indirectly. Two such indirect acoustic rays are shown in the figure. These reflections can be modeled as emissions from so-called *image sources* located outside the physical room boundaries. Image source positions are constructed by a mirror-symmetry operation with respect to a room boundary. Two image sources, associated to the two example reflections, are shown in the figure.

Many more image sources exist, like ceiling/floor reflections and higher-order reflections (e.g. wall–ceiling–wall). The combined effect of reflections can be observed in Fig. 2, which shows a processed acoustic measurement. The many peaks in this graph are caused by reflections, arriving at the receiver at different moments in time. Such a pattern of peaks was observed to be dependent on the 3D receiver position and orientation, given a fixed source position. These patterns were named *signatures* because they contain information about receiver position and orientation. The first peak in the signature corresponds to the line-of-sight distance between source and receiver. But from this one distance we do not know yet the receiver position. We would need more BSs for that. However, we expect that image sources can be used as if they are 'virtual base stations' (VBS). The combined information from BS and VBSs might enable estimation of the 3D receiver position. But the problem with VBSs is that we can neither identify nor distinguish them. For example, for the peaks in Fig. 2 it is not known by which VBS they were 'transmitted'. As a result, standard trilateration algorithms can not be applied, and it is very difficult to directly calculate a 3D position from a measured signature. However, the reverse is easier: computing an expected signature, given a 3D position. This fact is exploited by the *signature matching* method presented in Section IV.

III. Acoustical model

To compute an expected acoustic signature for a certain position in a room, a model is needed that describes the electrical and acoustical properties of the positioning system (including transmitter and receiver) and the acoustics of the room. Such a model is summarized in this section, more details can be found in [5].

A. Transmitter and receiver model

In our implementation, piezo-electric ultrasound transducers were used. Piezo transducers can be modeled by a linear impulse response [3]. In the model the combined transmitter and receiver impulse response $h_{\mathrm{TR}}(t)$ is used. It was obtained by measurement, although physical modeling [3] is also possible.

Most ultrasonic transmitters are directional, designed to emit acoustic energy mainly within a narrow beam from the front. Likewise, receivers are most sensitive at the front. This direction-dependent attenuation for both transducers is captured in the transducers model by the *normalised beampattern function* $D_N(\theta)$ of a circular piston [15], where θ is the angle with respect to the transducer axis. (The piston model was slightly modified to account for the effect of the piezo transducer's casing.)

B. Box-shaped room model

Rooms exist in many shapes, but domestic and office rooms are often approximately box-shaped. Therefore we used a box-shaped room model, which has six boundary surfaces (four walls, ceiling, and floor). The goal of the room model is to predict the impulse response of a room $h_{\mathrm{r}}(t, \mathbf{p})$ as a function of relevant parameters. These parameters, in vector $\mathbf{p}$, include the room dimensions (assumed to be known), transmitter/receiver positions and orientations, surface reflection coefficients, and room temperature and humidity. In practice, a room response is a function of other parameters as well, such as people/objects/-furniture in the room. However, a 'minimal' room model of an empty room can be constructed that only includes the six boundary surfaces and ignores the room's contents. This is a standard approach in room acoustics. To model a room the *image method* was applied, because for box-shaped rooms an impulse response for short durations can be calculated efficiently using the image model of Allen and Berkley [2]. Refer to Section II for the image sources concept or to [2, 10] for details.

The image method is based on the ray acoustics [10] approximation of acoustic waves. For ray acoustics models of arbitrarily shaped rooms, the room impulse response h_{r} in a time interval $[0, t_e]$ can be written as a sum of N independent rays arriving at the receiver:

$$h_{\mathrm{r}}(t, \mathbf{p}) = \sum_{i=1}^{N} a_i \cdot \delta(t - d_i/c) \qquad (1)$$

where d_i is the distance the i-th ray travels, of which ray d_1 is the line-of-sight ray the others are reflections, a_i is the amplitude of the i-th ray arriving at the receiver, c is the speed of sound and δ the Dirac delta function. Note that values d_i, a_i and c are functions of parameter vector $\mathbf{p}$. For a box-shaped room all d_i can be calculated according to [2], for known room dimensions. The amplitudes a_i can be described in terms of acoustic pressure, taking into account the attenuation over distance [3, 9], attenuation due to reflections, and the attenuation caused by the orientations of both transducers as modeled by the beampattern function (Section III-A).

The attenuation due to boundary surface reflections varies, depending on the reflection coefficient Γ of building materials. From measurements we observed that for typical building materials there is little reflection loss ($\Gamma \approx 1$) at ultrasonic frequencies around 40 kHz. However, for soft materials such as curtains or carpet (e.g. $\Gamma \approx 0.3$), the loss can be substantial. A default of $\Gamma = 1$ was used in the model.

C. Simulation of the model

The combined room/transducers model has one input signal u, which is the electrical signal applied to the transmitter, and one output y^e, the expected signal at the receiver. The output y^e is given by convolving the room model, transducers model and u:

$$y^e(t, \mathbf{p}) = h_{\mathrm{r}}(t, \mathbf{p}) * h_{\mathrm{TR}}(t) * u(t) \qquad (2)$$

IV. Signature matching method

In this section the *signature matching* method will be presented. It estimates the 3D position of a mobile device (MD) in a room, based on an acoustic measurement performed by the MD. One fixed base station (BS) is needed within the room. Because it is very difficult to directly estimate a 3D position directly from the signature (as noted in Section II), the method uses the reverse approach. It simply tries a set C of *candidate 3D positions* in the room, calculates an expected signature at these positions using the acoustic model of Section III, and compares those to the measured signature. Finally the best-matching candidate position is picked as the likely MD position.

A. Line-of-sight distance measurement

Measurement of the line-of-sight (LOS) distance between BS and MD gives initial information about the MD position. To obtain this LOS measurement, we assume that transmitter and receiver have mutual time synchronisation by an RF link similar to existing systems [1, 12, 13]. The LOS distance can then be obtained by a first-peak detection on the measured signature.

Figure 3 shows a front view of a room. For now, we assume that the fixed transmitter Tx near the ceiling acts as a BS and that the mobile device Rx is a receiver. The LOS distance is visualised as a line between them. The partial sphere surface S represents all possible positions of Rx, if nothing but the LOS distance and the coordinates of

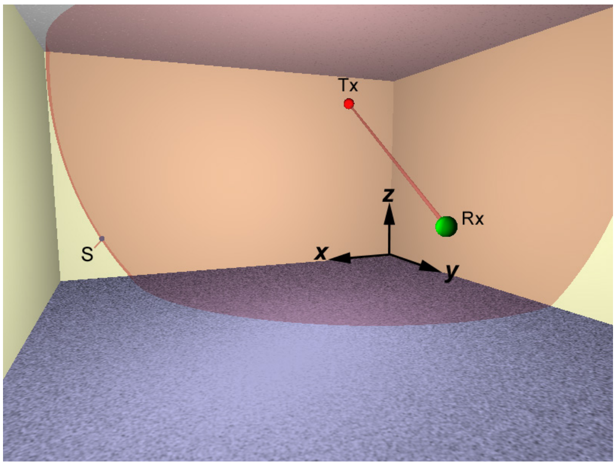

Fig. 3. 3D view of a room with transmitter Tx and receiver Rx.

Tx in the room are known. Using this knowledge, a set C can be constructed that contains N_c candidate positions, distributed evenly over surface S.

Note that measurement of the LOS distance could fail due to blocking of the line-of-sight path. In this paper it is assumed that LOS measurements always succeed. During test measurements, this was also assured by measuring in an empty room. The failure case is discussed in [6] in the context of another single-BS positioning method.

B. Signature matching algorithm

The signature matching algorithm takes a measured signature vector $\mathbf{s}$ as input and produces a position estimate $\hat{\mathbf{x}}$ of the MD.

Certain parameters must be known before the algorithm can be executed: the first group of parameters are the configuration parameters $\mathbf{p}$ (Section III-B), describing the physical circumstances within the room. The room size (part of $\mathbf{p}$) can be obtained by manual input, or estimated through echo measurements by the fixed BS. Furthermore the 3D position and orientation of the BS should be known. Finally we need the orientation vector $\mathbf{v_R}$ of the transducer mounted on the mobile device. $\mathbf{v_R}$ should be seen as the 'pointing direction' of the transducer. Three options were identified to obtain $\mathbf{v_R}$: first, the orientation could be 'fixed by design'. An example is a remote control unit that is mostly lying horizontally on a table surface or held in hand, with the transducer approximately pointing up. A second option is to estimate orientation, making use of characteristics of the measured signature. Methods to do so are in development. A third option is to use gravitational and/or inertial orientation sensors within a MD to estimate (part of) the orientation.

The second group of parameters are the algorithm parameters. These include e.g. the size of the set C of candidate positions, and the choice of a metric to use for matching.

The signature matching algorithm [5] proceeds as follows: for a measured signature $\mathbf{s}$, first the LOS distance is determined, and second the set C of candidate positions is created on surface S, as shown in the above section. Third, for all candidate positions in C an expected signature $\mathbf{s}^{\mathbf{e}}$ is calculated using the acoustic model. Fourth, all signatures in C are matched to $\mathbf{s}$, and the best matching candidate j with position $\mathbf{x}_j$ is picked as the likely MD position, $\hat{\mathbf{x}} = \mathbf{x}_j$.

C. Comparison metrics

A *comparison metric* is a method of matching two signatures. It is defined as a function $m = f(\mathbf{x}, \mathbf{y})$ of two signature vectors $\mathbf{x}$ and $\mathbf{y}$ to compare, with a scalar outcome m. The maximum value of m, over all $\mathbf{x}$ and $\mathbf{y}$ to compare, is associated with a 'best match' of two signatures. So the higher m, the more $\mathbf{x}$ looks like $\mathbf{y}$.

Many comparison metrics are possible, for example mean absolute error, mean squared error, or pattern matching approaches. The first metrics tried were based simply on mean absolute difference between the signatures, which can be calculated quickly. These metrics are described by:

$$M_q(\mathbf{x}, \mathbf{y}) = -\frac{1}{N} \sum_{k=1}^{N} |x(k) - y(k)|^q \tag{3}$$

where q is a parameter to be chosen. The best match occurs when $\mathbf{x} = \mathbf{y}$, yielding maximum match value $M_q = 0$. Note M_1 is the mean absolute error metric and M_2 the mean squared error metric. Other comparison metrics are currently in development, for example a cross-spectrum based metric.

D. Discussion

The method and algorithm as presented, should be seen as an initial result. The computational load of the method is currently high (see Section V-D) and has to be improved. Another drawback is the need to know the orientation of the receiver $\mathbf{v_R}$. Furthermore, the sensitivity of the position estimates to changes in the algorithm's many parameters is still to be investigated.

V. IMPLEMENTATION

The signature matching method has been implemented as a measurement setup, built with two goals in mind. The first was to validate the room model against a real (empty) room. The second was to prototype an ultrasonic single-BS positioning system that uses the signature matching

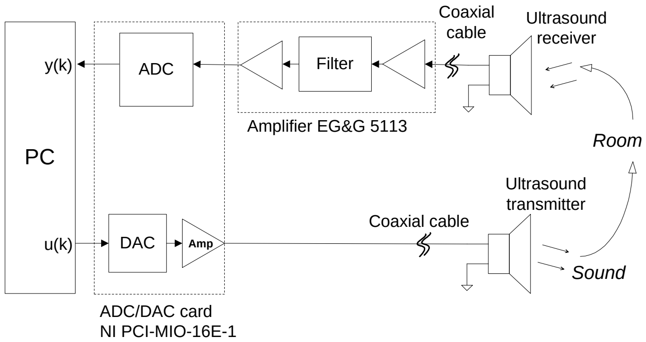

Fig. 4. Measurement setup diagram.

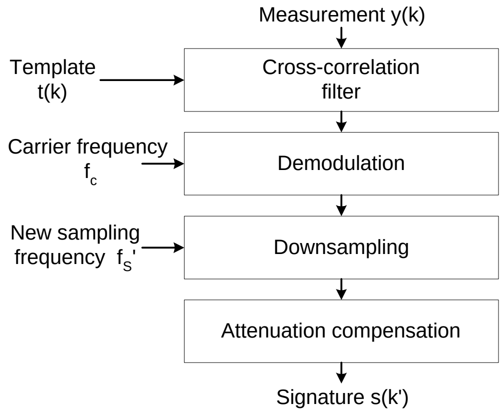

Fig. 5. Signal processing operations to obtain a signature.

method, and test its performance. In this section the measurement setup and signal processing steps are described.

A. Measurement setup

A choice that had to be made is whether the BS is a transmitter or a receiver. It was chosen to be a transmitter, which allows unlimited mobile receivers without risk of acoustic interference. The BS was implemented as an ultrasonic transmitter attached to a pole. The pole can be placed within a test room at a fixed position. One mobile device (MD) was implemented as a receiver attached to a pole. It can be moved around to measure at various positions and orientations in 3D space.

The measurement setup diagram is shown in Fig. 4. One transmitter for the BS and one receiver for the MD are connected to a measurement PC. The output DAC drives a Quantelec SQ-40T 40 kHz ultrasound transmitter with sinusoidal bursts within ± 3 V. The acoustic waves propagate inside the room, and are recorded by a Quantelec SQ-40R receiver. The received electrical signal is amplified, and filtered by a 30-100 kHz bandpass filter to remove electrical noise. The ADC samples the data $y(k)$ and sends it to the PC running MATLAB. Time synchronization between BS and MD is simulated by a shared time trigger between the ADC and DAC.

B. Signal processing

The measured signal y is not used directly as input to the position estimation algorithm. A number of operations are performed to generate a *signature*, which is the input to the algorithm. The signature contains all relevant information of the measurement in a compact form. Figure 5 shows the operations performed in MATLAB to obtain a signature. The first step is a cross-correlation filter, that performs matched filtering to remove noise and also produces correlation output peaks signifying the times-of-arrival of acoustic wavefronts at the receiver. The template $t(k)$ is the signal as expected to arrive from a single acoustic ray, obtained using the transducers model (Section III-A). The second operation demodulates an amplitude envelope from the ultrasonic signal's $f_c = 40$ kHz carrier frequency. Since the bandwidth of the envelope is less than 10 kHz, it is downsampled in the third step by a factor 10 to sampling frequency $f_s = 25$ kHz. The fourth step is attenuation compensation, which compensates the typical signal amplitude attenuation of ultrasound over distance. Without this step, a signature's appearance would be dominated by the first few early-arriving reflections, which are higher in amplitude than late-arriving ones. The compensation step allows for a fair comparison between two signatures when using amplitude-based metrics as in Eq. 3.

The result is a signature $s(k')$ which has a typical peak and valley pattern, where each peak signifies the arrival of one or more acoustic rays at the receiver at that moment in time. It can also be written as a signature vector $\mathbf{s}$. For an example signature see Fig. 2.

C. Signature calculation

A straightforward calculation of an expected signature s^e involves simulating the acoustic model using Eq. 2, and processing result vector y^e according to the steps above. But to reduce the calculation time of convolutions in MATLAB, an optimization was performed based on a Fourier transformation of Eq. 2 to the frequency domain:

$$Y(f) = H_{\mathrm{r}}(f, \mathbf{p}) \cdot H_{\mathrm{TR}}(f) \cdot U(f) \; . \tag{4}$$

Define s^e as the signature calculated from y^e, and S as its Fourier transform. Then the cross-correlation of y^e with template t (having spectrum T) and demodulation (from carrier frequency f_c) are equivalent to:

$$\begin{aligned} S(f) &= T(f_c - f) \cdot Y(f - f_c) \\ &= H_{\mathrm{r}}(f - f_c, \mathbf{p}) \cdot U'(f - f_c) \; , \end{aligned} \tag{5}$$

where Eq. 4 was substitued for Y and the newly defined

$$U'(f) = T(-f) \cdot H_{\mathrm{TR}}(f) \cdot U(f) \tag{6}$$

is indepedent of parameters $\mathbf{p}$ so it only has to be calculated once.

The signature calculation then proceeds as follows: first, H_{r} is calculated by applying a FFT to h_{r}. After the vector multiplication of Eq. 5, the 'uncompensated' signature s^e is obtained by applying an IFFT to S. Finally, the attenuation compensation step is applied to s^e by another vector multiplication.

D. Algorithm computational load

The signature matching algorithm was implemented using the M_1 comparison metric. The computational bottleneck of the algorithm in this case is the simulation of signature vectors $\mathbf{s^e}$ for each of the N_c candidate positions in set C, using Eq. 5. One simulation involves a N-point FFT, vector multiplication, and IFFT operation, where N=4096 currently. The full computational load is approximately $O(N_c{\cdot}10^5)$ FLOPS for a set C of size N_c, where N_c ranged from 7243 to 11131 in our experiments, depending on the varying surface area of sphere S. This implies a calculation time of 1-10 s for an optimized implementation on a Pentium 4 PC. The calculation time could be significantly reduced by a smarter choice of C, e.g. using optimization algorithms or pruning of the search space.

VI. Experimental

Initial experiments were performed in an empty office room. An empty room was chosen to verify the acoustic room model. Also, an empty room represents the best-case condition for any location system. Experiments in a room with obstacles are planned.

A. Experimental procedure

The test room size is 3.73 by 7.70 m and 2.97 m high. Some irregularities are present in the form of windows, window-ledges, a door, radiator, a tap and sink, and ceiling-embedded lighting units. A coordinate system was defined as shown in Fig. 3. The BS position $(0.95, 0.04, 2.95)$ near the ceiling was used, to mimic the typical ceiling placement for indoor location systems. The receiver was placed at several positions in the room as shown in the next section. The height of the receiver was set at 1.3 meter, to mimic a typical height for a mobile device that is carried around in a user's hand. The orientation of the receiver was always set parallel to the negative y axis, i.e. $\mathbf{v_R} = (0, -1, 0)$, ensuring a good LOS path between transmitter and receiver.

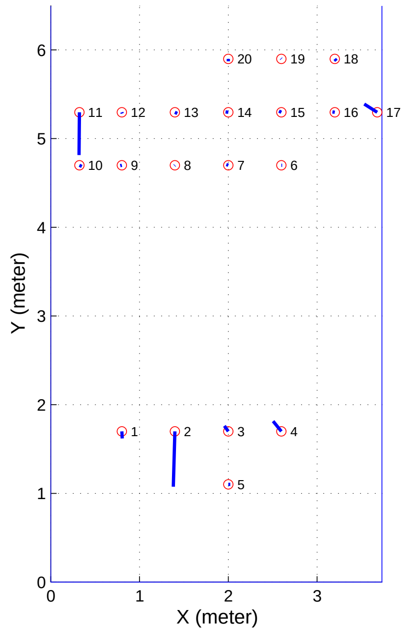

Fig. 6. Top view of the test room, showing 20 measurement locations (encircled). The position estimates per position are shown by the tips of the solid lines.

B. Results

The signature matching algorithm was executed for 20 measurements in total at various positions in the test room. These positions are shown as circles in Fig. 6 in an XY top view of the room. In the same figure, the estimated positions are marked by lines pointing from the encircled true positions towards the estimated positions. It can be seen that accuracy is usually better than 20 cm, except for positions 2 and 11. They have a larger position error, but still within the limit of ≤ 1 m. These errors were caused by a combination of three effects in the measured signature: 'missing' peaks, unexpected spurious peaks, and random deviation of peak-amplitudes from their predicted values.

C. Discussion

It can be expected that the above error effects become more frequent, if more objects and obstructions are present in the room. The more objects clutter a room, the less valid the model of an empty room will become, which could degrade positioning accuracy. Tests are needed for the realistic case of a cluttered room. Likely, the method itself has to be improved to cope with these situations.

VII. Conclusions

Based on the experimental work it can be concluded that measured ultrasonic signals contain more information than just the transmitter-receiver line-of-sight distance. In existing ultrasonic location systems, only the latter is used.

The extra information is contained in a measured pattern, the *signature*. The signature consists of amplitude peaks, that are caused by acoustic reflections within a room.

We propose to use the information contained in the signature to perform 3D device position estimation, using just a single base station per room. A method called *signature matching* was designed and implemented for this purpose. It was shown by initial experiments that the signature in an empty room can be predicted by an acoustic model with sufficient accuracy to use it for 3D position estimation.

The method described in this paper is not yet mature. Future work is aimed at applying the method in realistic non-empty rooms. This requires improvements to the method as mentioned in Section VI-C. A first improvement is to implement a *tracking* system, that integrates a set of position estimates over time for improved accuracy and robustness. Second, the use of acoustic reflections could be combined with the single-BS array position estimation method in [6]. Such an array allows a base station to get more information about the direction of mobile devices, thus enabling more robust position estimates. Third, the computational load of the method has to be improved, as the current 'brute force' approach takes too long for real-time position estimates.

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