Human-Assisted Calibration of an Angulation based Location Indoor System with Preselection of Measurements

Jürgen Kemper, Nicolaj Kirchhof, Markus Walter
Robotics Research Institute
Technische Universität Dortmund
Otto-Hahn-Str. 8
44227 Dortmund, Germany
Email: {juergen.kemper, nicolaj.kirchhof, markus2.walter}@tu-dortmund.de

Holger Linde
Ambiplex GmbH & Co. KG
Idastr. 11
44388 Dortmund, Germany
Email: holger.linde@ambiplex.com

***Abstract*—Besides aspects like accuracy and cost, a simple setup process is essential for the adoption of location systems. However, existing systems often require a time-consuming calibration process to determine sensor node positions or orientations. In this paper we present a software aided approach for the calibration of an angulation-based indoor location system, which only demands from the user to walk through the room. The novelty of the presented approach is that a completely passive sensor technology is applied whereas the calculations are exclusively based on angular measurements. The node localization is realized without any prior knowledge of sensor positions, orientations or the location of the moving person. Nevertheless, it can be shown that an accurate localization of the sensor nodes is possible. The presented algorithm is based on the Newton-Raphson method for solving non-linear equation systems. In order to improve the calibration results, a preselection of the calibration measurements is processed that realizes the identification and non-consideration of unreliable measurements. The accuracy of the approach, its convergence probability and its runtime are evaluated by several simulations. Furthermore, real-world tests, using a location system that exploits the thermal radiation of humans for localization, are carried out to verify the simulation results.**

***Keywords*-Human Assisted, Calibration, Localization, Infrared, Thermal, Thermopile, Tracking, Auto-Calibration**

I. Introduction

The ability to locate people is an essential prerequisite to enable *location-based services*. Therefore, in recent years, several indoor location systems for the field of ubiquitous computing have been developed [2]–[4]. Dependent on the used technology like infrared [5], [6], radio [7]–[9] or ultrasound [10], [11] these systems differ in aspects like accuracy, scalability and cost, whereas especially the latter have direct impact on the acceptance of such systems.

Indeed, the costs of a system do not only depend on the required hardware but also on the installation effort, which corresponds to the time for setting up a system. This time is influenced by the number of sensors, which have to be installed and the time, needed for system calibration, that is, to determine the sensor nodes positions and where needed, their orientation. The number of required nodes depends on their field of view (FoV) and their range. For a cost-efficient localization solution as few sensor nodes as possible should be used.

The calibration effort, on the other hand, is strongly related to the accuracy of the systems. For example, the accuracy of proximity-based location systems such as Active Badge [5] is often limited to room size. Here, the sensor node position is not crucial and therefore, deployment efforts are low.

Contrary to this, lateration-based systems require exact knowledge about the node positions in order to enable accurate localization. Hence, often a time-consuming manual measurement process is required. When additionally applying angulation, besides the exact position also the orientation of the sensor nodes has to be known. Due to this costly calibration, many of the proposed location systems are not practical and therefore suffer from the lack of acceptance.

Automated node localization can help to reduce the effort of calibration significantly. Instead of measuring the sensor coordinates manually, pairwise node distances or other geometrical relations are ascertained by the sensor nodes themselves. From these measurements the sensor coordinates are subsequently calculated. To enable automated calibration, nodes must be able to detect each other. For instance, in a radio location system, they must be equipped with both receivers *and* transmitters.

In the past, especially in the field of *wireless sensor networks*, an essential contribution to autonomous node localization was made. However, these approaches are mostly intended for sensor networks that consist of many nodes and cover a huge area. Indoor location systems on the other hand are often limited to one or a few rooms. Consequently, the requirements for node localization are quite different indoors. In particular, a high position accuracy of the sensor nodes is demanded. This fact implicates that automated calibration is infeasible in certain approaches. E. g. radio location systems estimating distances based on received signal strength (RSS) measurements usually yield a location error of far above one meter. Due to this low accuracy, calibration must be performed manually.

If a passive positioning technology is used, which implies that the sensor nodes are only equipped with receiving elements, distance measurements between sensor nodes are not feasible at all. A promising approach to overcome this problem is *mobile assisted* calibration [12]. Following this approach, a mobile source moving through the room is used to enable the required measurements. However, in that case, not the pairwise geometrical relations between the nodes are measured but those between the mobile source and the nodes.

In this paper, a mobile assisted calibration approach for an angulation-based location system is presented. This system exploits the thermal radiation of humans for localization. It is entirely passive, which means that the sensor nodes are equipped with infrared *sensors* only. Hence, an assisted node localization is required, in which a human acts as *mobile source* himself. Thus, we speak of human-assisted calibration. Furthermore, as infrared radiation does not penetrate walls, the location system is limited to one room and the number of required sensors is small.

For calibrating the system, the node positions and the node orientations have to be determined. The novelty of the presented approach is that a completely passive sensor technology is applied whereas the calculations are exclusively based on angular measurements. The node localization is realized without any prior knowledge of sensor positions, orientations or the location of the moving person. Nevertheless, it can be shown that an accurate localization of the sensor nodes is possible.

The aim of the proposed approach is to significantly reduce the calibration effort of the system by automating the process of node localization. Without automation the calibration is very costly, especially the determination of the sensor orientation. The described approach, however, enables the user to calibrate the system by walking through the room.

The remainder of the paper is structured as follows. In Sect. II related work is discussed. In Section III the ideas and the algorithm to realize human-assisted calibration are described. The process of calibration and some essential software requirements are presented in Sect. IV. In Sect. V experimental and simulation results are discussed. Finally, in Sect. VI a conclusion is drawn and an outlook on future work is given.

II. Related Work

As already stated, in recent years, several indoor location systems have been developed. However, the aspects of calibrating such systems have rarely been addressed.

General approaches were discussed for large-scale sensor networks. Mostly, they are based on distance measurements between sensor nodes. Unknown node positions are calculated via trilateration based on known node positions and the measured distances between these nodes and the unknown ones. Anchor-based algorithms start with a few known sensor positions to calculate all unknown ones with respect to a global coordinate system. In contrast to that, anchor-free algorithms try to determine the network structure without initial anchor nodes. Thus, the calculated system geometry is ambiguous, therefore translation, rotation and flipping is still possible. Both types of algorithms suffer the problem that for spare distribution of nodes no unique structure can be determined. The calculations themselves can either be done incrementally or concurrently. In the prior case, the algorithm starts with a set of three or four nodes to calculate unknown node positions and obtains a new node position in every iteration step. In the latter case, all node positions are concurrently optimized. The advantage of this approach is that the propagation of measurement errors and the probability of being stuck in a local minimum is lower. Finally, centralized (computation on a workstation) and decentralized (by the nodes) approaches have to be distinguished.

Motivated by the *Smart Dust* project, Doherty et al. [13] developed a centralized, anchor-based approach. It derives unknown node positions from proximity and angular constraints between beacons, given by their connectivity. A global solution is found by a linear-programming algorithm working on a network representation of a set of convex position constraints.

A distributed, anchor-based approach (APS) was described by Niculescu and Nath [14] that applies RSSI (**R**eceived **S**ignal **S**trength **I**ndication) and trilateration. For node localization they discuss different methods. In their *DV-hop method* the number of hops between anchor nodes are measured to calculate an average hop distance. Afterwards, the node positions are calculated by trilateration exploiting the hop and distance information. The resulting accuracy is limited to 45 % of the radio range. In contrast to that, the *DV-distance method* estimates the distances between nodes by RSSI measurements and reduces the error by 50 %. An additional paper by both authors [15] deals with a similar approach but instead of trilateration triangulation is used to determine the network structure. The resulting non-linear problem is reduced to a linear one, again based on trilateration.

A mobile-assisted, anchor-free node localization approach was proposed by Sichitiu and Ramadurai [16]. They used a PDA equipped with GPS and WLAN to measure the distance to different nodes at several positions based on RSSI and applied a method using Baysian inference for information processing, afterwards. Experimental results revealed a node localization error of less than 3 m.

Another anchor-free approach, using mobile robots for node localization was presented by Pathirana et al. [17] By applying RSSI measurements and a Robust Extended Kalman Filter-based state estimator for node localization, they were able to realize an accuracy of approximately 1 m, which demands the availability of precise odometry information of a robot.

A general survey of different approaches for indoor location systems was given by Scott and Hazas [18]. Using the *Active Bat* system, they examined three different data gathering methods: Placing several nodes on a mobile frame, whereas the relative locations are known, placing several nodes on the floor and gathering measurements data while a human moves around. For the calculation of node positions non-linear regression was applied. Experiments showed that the frame-based approach in combination with non-linear regression provides the highest accuracy with a mean error of 3 cm. In contrast to that, the human-assisted method exhibits a mean accuracy of 19 cm.

A distributed, anchor-based indoor localization approach using collaborative multilateration was described by Savvides et al. [19]. They showed that the use of ultrasound in combination with ToA (**T**ime **o**f **A**rrival) and trilateration is a sufficient candidate for fine-grained localization. Starting with several anchor-nodes, the unknown node positions are calculated with an over-constrained set of equations. Experiments showed that node position errors of less than 20 cm with a sufficient number of nodes are possible. However, due to the incremental calculation process, error propagation has to be considered.

A mobile-assisted, anchor-free approach without knowledge about the position of the mobile unit was proposed by Priyantha et al. [12]. The authors used the well known *Cricket* system and a mobile robot equipped with a cricket node for their evaluation. By utilizing the robot, they were able to overcome the problems of line-of-sight obstruction and ambiguity due to sparse node deployment. In order to gather appropriate distance samples to solve the localization problem certain movement constraints were developed. Experimental results showed that the median pairwise distance error is less than 1.5 % of the distance between the nodes.

III. THEORY OF CALIBRATION

Before describing the developed calibration algorithm in detail, first of all, the used location system and the resulting requirements are outlined.

A. Passive Infrared Localization

Passive infrared location systems exploit the thermal radiation emitted by humans to determine their position. As sensing elements so called thermopiles are used, which consist of a series connection of thermocouples. If several of those thermopiles are combined to a line or array sensor, whereas every pixel exhibit a slightly different field of view, it is possible to measure the angle under which an object is seen. As illustrated in Fig. 1, the basic principle for

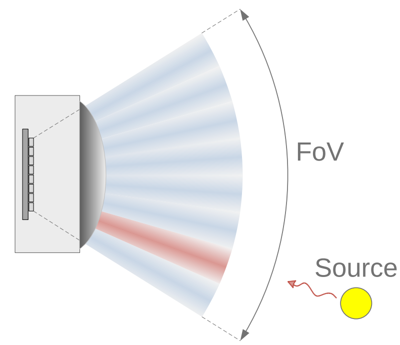


Figure 1. Principle of AoA estimation

determining this angle of arrival (AoA) is to choose that one, which corresponds to the line-of-sight of the pixel with the highest outcome.

The location system described by Kemper et al. [4] consists of special thermopile modules developed by *Ambiplex* [20]. These modules are capable of detecting heat sources within an angular range of 48° and 90°, respectively. In the second case two line sensors with a field of view of 48° are attached to the module (double sensors). At a typical room temperature of 22 °C, the angle between the sensor and a heat source – typically a human being – can be detected up to a distance of 10 m with a angular accuracy of $\pm 2°$. For environment temperatures up to 26° the overall system accuracy stays nearly constant, with a mean position error of 15 cm. Higher temperatures than 26° lead to a rapidly increasing position error, because the received radiation is almost indistinguishable from the natural senor noise.

In order to calculate the AOA, a more elaborate algorithm is used that yields a higher resolution by exploiting the fact that the radiating source is typically seen by more than one pixel. Besides the angle of arrival it also calculates a quality measure for the AoA, denoted the *Score*.

In order to set up a location system, several of these modules have to be deployed in a room, e. g. in the corners at chest height. For a room of up to 7×7 m, four double sensors with a field of view (FoV) of 90° are sufficient as illustrated in Fig. 2.

B. The node localization problem

After describing the used location system, subsequently we take a closer look on the resulting localization problem:

The one-dimensional angle of arrival provided by the sensors results in a two-dimensional localization problem. A human-assisted node localization is required, as the sensor nodes do not emit signals that can be exploited for mutual detection. In addition, this type of system requires a centralized approach as the sensors' computational power is extremely limited. Moreover, after installing the sensor

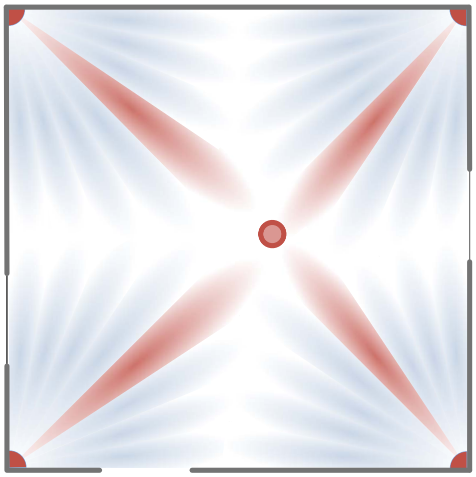


Figure 2. Typical sensor placement

nodes neither their position nor their orientation is known. Consequently, a concurrent, centralized and anchor-free approach seems to be the best choice to realize the calibration. The drawbacks of a centralized approach like the required computational power are negligible since the calibration has to be processed only once. Additionally, in comparison to most of the approaches described in Sect. II, the number of required nodes is small, as thermal radiation does not penetrate walls and the calibration has to be done room by room.

C. Human-Assisted Node Localization

As comfort was the main objective for the development of an automated calibration procedure, the contribution demanded from the user to calibrate the system was supposed to be as small as possible. Therefore, the idea of calibrating a system by walking through the room was considered to be the easiest and most practicable way. The developed algorithm to realize this kind of calibration is described subsequently.

Fundamental Geometrical Relations: Before explaining the used algorithm, first of all, the fundamental geometrical relations of the localization problem have to be described. Figure 3 illustrates these relations and the denotation of variables. Sensors are denoted S_i, where $0 \leq i < N$ and N is the number of sensors. Their positions and orientations with respect to the x-axis are given by $(x_{S_i}|y_{S_i})$ and Θ_{S_i}, respectively. During calibration, the system notifies the user to remain still at a M arbitrary positions P_j, with $0 \leq j < M$. These positions are referred to as *source locations*. Their coordinates are $(x_{P_j}|y_{P_j})$. Finally, the angle under which source location P_j is "seen" by sensor S_i is denoted $\varphi_{S_iP_j}$. The geometrical relation between S_i and P_j can be expressed using the tangent:

$$\tan(\theta_{S_i} + \varphi_{S_iP_j}) = \frac{y_{P_j} - y_{S_i}}{x_{P_j} - x_{S_i}} \tag{1}$$

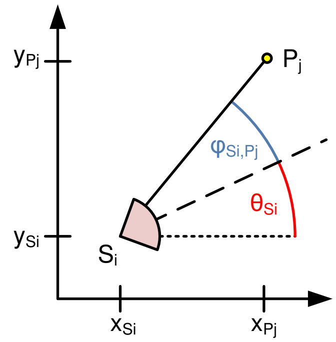


Figure 3. Geometric relations and denotation

After applying some mathematical transformations and the substitution of $\tan(\varphi_{S_iP_j})$ by t_{ij}, a non-linear equation for the calibration algorithm is obtained. This equation exhibits five unknowns x_{P_j}, y_{P_j}, x_{S_i}, y_{S_i} and Θ_{S_i}

$$\begin{aligned} 0 \;=\; & -t_{ij}x_{S_i} + y_{S_i} + (x_{P_j} + y_{P_j}t_{ij}) \cdot \tan\theta_{S_i} \\ & -x_{S_i}\tan\theta_{S_i} - t_{ij}y_{S_i}\tan\theta_{S_i} + x_{P_j}t_{ij} - y_{P_j} \end{aligned} \tag{2}$$

Solvability: If the equations for every sensor-source location combination is set up, a non-linear system with a maximum number of equations $K_E = N \times M$ is obtained. However, in practice, the overall number of equations is lower since, dependent on the sensor setup, not all positions are in the field of view (FoV) of any sensor. Furthermore, for non-linear systems of equations (NLSE) no general prediction of solvability is possible. Nevertheless, for our further considerations, we assume that a solution exists, if the number of independent equations is equal or greater than the number of unknowns. The latter is given by

$$NR_u = 3N + 2M, \tag{3}$$

since every sensor module exhibits three and every source location two unknowns.

To be a bit more problem specific, for every sensor at least three measurements at different positions are necessary (three unknowns per sensor), whereas at every source location the measured object has to be seen by more than two sensors as the source locations are unknown. Table I shows the difference between the number of variables and the unknowns when all positions are in the FoV of every sensor. Unfortunately, this cannot be fulfilled in general. However, the table clarifies that only measurements seen by more than two sensors have a contribution in the reduction of unknowns. Hence, if only these measurements are considered and at least nine valid measurements for every sensor exist, it should be possible to find a solution. In most cases fewer measurement positions are required if at least one of them is in the FoV of more than three sensors. In practice, the number of unknowns is reduced by four since the position and orientation of one sensor should be set as

		N (Sensors)				
		1	2	3	4	5
M (Positions)	4	-7	-6	-7	-4	-3
	5	-8	-6	-4	-2	**0**
	6	-9	-6	-3	**0**	**3**
	7	-10	-6	-2	**2**	**6**
	8	-11	-6	-1	**4**	**9**
	9	-12	-6	**0**	**6**	**12**

Table I
DIFFERENCE BETWEEN NUMBER OF EQUATION AND VARIABLES

reference as well as the distance between this sensor and another one to obtain an unambiguous solution.

If using double sensors instead of single ones as done in the experiments later on, the number of unknowns per module increases to four. Consequently, the number of required source location rises, too.

The Calibration Algorithm: Due to its complexity the resulting NLSE cannot be solved analytically but numerically. The Newton-Raphson method is one of the most efficient approximation procedures for differentiable mappings [21] and can also be applied to multi-dimensional equation systems. The basic idea of this method is to find the root of an equation system of the form $\vec{f}(\vec{x}) = \vec{0}$ by an iterative approximation. Starting with an initial guess, the function is approximated by its derivative at this position. In a second step the root of this derivative is calculated. If the initial guess is near the real solution, the current approximation will typically be better than the former one.

For every step the following LSE has to be solved to obtain the current iteration step $\Delta\vec{x}$:

$$J(\vec{x}_i) \cdot \Delta\vec{x} = -\vec{f}(\vec{x}_i), \quad (4)$$

where $J(\vec{x}_i)$ is the Jacobian matrix and contains the partial derivatives of $\vec{f}(\vec{x}_i)$. Consequently, $\Delta\vec{x}$ can be calculated applying the inverse of $J(\vec{x}_i)$

$$\Delta\vec{x} = -J(\vec{x}_i)^{-1} \cdot \vec{f}(\vec{x}_i) \quad (5)$$

so that finally the assumption for the next iteration can be calculated as

$$\vec{x}_{i+1} = \vec{x}_i + \Delta\vec{x}. \quad (6)$$

In every step the error e of the current approximation is given by the Euclidean norm

$$e = \left\| \vec{f}(\vec{x}_i) \right\| \quad (7)$$

of $\vec{f}(\vec{x}_i)$ at the current position $\vec{x}_i$. Moreover, e can be used as a fitness function. The iteration process can be stopped once the difference of e between two iteration steps falls under a certain limit. However, dependent on the initial guess it may happen that only a local minimum is found or the approximation does not converge at all. In this case, another calculation with a different initial guess has to be started. It is obvious that the initial values of the iteration process are crucial for the convergence of the Newton-Raphson method. However, due to the high-dimensional solution space, finding an adequate initial guess is very complex. Therefore, in the current implementation, we decided to generate it randomly.

Enhancements due to Practical Requirements:: In practice, measurements are not ideal due to sensor noise and systematic errors. Thus, averaging is applied to reduce the impact of noise during calibration, which means that several measurements are carried out while a human is standing still at one position. Averaging over these measurements finally results in a less noisy value.

The impact of faulty measurements, on the other hand, can be reduced by over-determination and calculation of a best fit solution (least squares). That is, the NLSE is composed of more than the required number of equations, for which reason additional measurements and hence additional source locations are required.

In case of having an over-determined NLSE, instead of the inverse of $J(\vec{x})$ the pseudo-inverse

$$J^{+} = (J^T J)^{-1} J^T \quad (8)$$

has to be applied. Since with every new equation the complexity of the problem is increased, an optimal grade of over-determination has to be found. To check this, we did some evaluations. The results are presented in Sect. V. It should be noted that the complexity of the approach is O(n^3) for every iteration step, where n denotes the number of equations. The computation is dominated by the LU-decomposition for matrix inversion. However, since the calibration has to be processed only once and off-line, the runtime of the algorithm is not crucial as long as it is significantly faster than the manual calibration.

D. Preselection of Measurements

Due to the limited range of the used sensors and the applied algorithm that exploits that the radiation of a human is typically received by more than one pixel, the accuracy of the measured angle decreases with increasing distance between object and sensor.

Additionally, an erroneous AoA is calculated if a human is only partially covered by the FoV of a sensor. This is caused by the fact that the AoA is typically assumed to be in the middle of the covered part. Consequently, this error increases with decreasing distance between radiation source and sensor. Table II illustrates this error for a human located at the edge of the FoV of one sensor (24°) and different distances. It can be seen, that at a distance of 0.5 m the measurement error is almost 13°, which is very problematic for calibration, as high errors may lead to bad calibration results or to a non-solveable NLSE, either.

Distance	3 m	2 m	1 m	0,5 m
AoA	24°	22.9°	18.8°	11.1°

Table II
ERROR DUE TO PARTIAL COVERAGE

In order to avoid the negative impact of measurements that are erroneous due to the described reasons their non-consideration is convenient. For the identification of these measurements some kind of quality measure is required. For this purpose the already mentioned *score* can be used. It is calculated along with the AoA and decreases with increasing distance between sensor and source. However, evaluations have shown that this score is very noisy and highly non-linear with respect to distance as Fig. 4 illustrates.

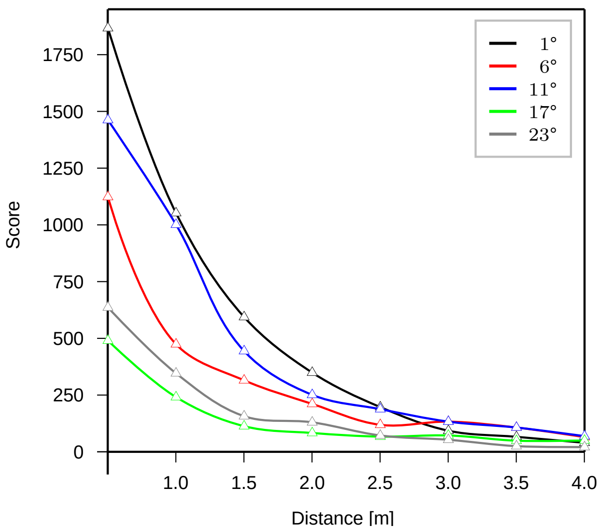


Figure 4. Score values with respect to distance and measured angle

Furthermore, it depends on the object size, its temperature and the AoA itself. Thus it is not very reliable and therefore only used as a threshold criterion. That means that a measurement is valid if its *score* is within a certain interval and rejected if not. In case of the later described real-world tests the limits were determined empirically and set to

$$50 \leq Score_{valid} \leq 1500. \tag{9}$$

IV. PROCESS OF CALIBRATION

In addition to an adequate algorithm to locate the sensors, certain requirements must be met in order to enable a comfortable and successful calibration.

A. Software Requirements

As described in Sect. III-C, due to sensor noise, it is necessary that the user, who calibrates the system, stands still at a random position. The position must be chosen in a way that enough information is gathered to calibrate all sensors. Hence, a convenient calibration software has to guide the user with respect to the following aspects. The system should inform the user,

- when to move and when to stand still.
- when enough information is gathered.

In order to meet these requirements, we developed a calibration software that realizes this signalling by sound. After starting the calibration process and entering the room, the software notifies by a deep beep that the user should stop moving. After a short period of time a high beep indicates that this measurement is finished and that the user should continue moving around until another deep beep instructs him to stop. This procedure is repeated until enough information is gathered, which is reported by a high double beep. To realize this kind of calibration two further conditions must be fulfilled. The software must be able to detect, whether the user is standing still or moving, and whether he has moved far enough.

The detection of movement is realized by considering the changes in the measured AoAs. If all of them fall steadily under a certain threshold, it is likely that the user has stopped moving. On the other hand, the decision whether the user has moved far enough to process a new measurement is based on the AoAs. That is, if the change in at least one of the measured AoAs is steadily greater than a certain threshold, e. g. 2°, a new measurement can be processed.

Concurrently, the former described preselection process takes place. So measurements with a score outside the limits are directly rejected. If furthermore less than two measurements remain for one source location, it is rejected completely.

B. Convergence and Local Minima

After gathering the measurement information, the sensor poses have to be calculated. However, as already described, two problems may occur: First, due to the initial guess only a local minimum might be found and second, the calculation could not converge at all. The latter case can easily be detected by the software itself, which stops the iteration after a while, if no convergence is noticeable. The calculation is then restarted with another initial guess.

Due to measurement errors and the use of an over-determined NLSE the calculated solution is not a *root* anymore but a best fit of the NLSE. Consequently, an indicator is required to identify whether the found solution is only a local or a global minimum. We realized this indication by a plausibility check, as illustrated in Algorithm 1. This check is based on the assumption that a reasonable solution is found when the average of the difference between the measured AoAs and the ones computed with the calculated poses and measurement positions falls under a certain limit. In other words, the solution fits the measured angles. This average is computed separately for every sensor over all measurements. A sensor pose is considered valid if the

Algorithm 1 Plausibility Check

Require: $angle_{meas}[1..N, 1..M]$, $angle_{calc}[1..N, 1..M]$ and threshold
  for $i = 1$ to N **do**
    avg_i = 0;
    for all $k = 1$ to M **do**
      if $angle_{meas}[i, k]$ is valid **then**
        $avg_i + = |angle_{meas}[i, k] - angle_{calc}[i, k]|$
        $p = p + 1$
      end if
      $k = k + 1$
    end for
    $avg_i = \frac{avg_i}{p}$
    if $avg_i > threshold$ **then**
      return $false$
    end if
    $i \leftarrow i + 1$
  end for
  return $true$

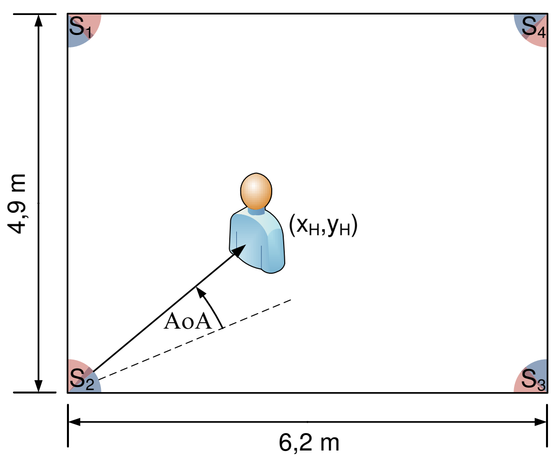


Figure 5. Testbed

computed average is smaller than a given threshold. The overall solution is accepted if all sensor poses are valid.

V. Experimental Results & Simulation

In order to test the developed algorithm, several simulations were conducted. Furthermore, our approach was tested in a real-world scenario.

A. Experimental Results

In order to make some real-world tests, we set up a location system consisting of four double-sensor modules placed at chest height in the corners of a room of $6.2 \times 4.9\,\mathrm{m}^2$, as Fig. 5 depicts.

Since every source location is in the FoV of every double-sensor six different location measurements would have been sufficient (four variables per sensor pair; cf. Sect. III-C). However, due to measurement noise and in order to evaluate the effect of an over-determined calibration, measurements with 15, 18 and 21 different source locations were carried out, each with five passes. Table III illustrates the absolute mean position errors (MPE) in centimeter and the absolute mean orientation errors (MOE) in degree of the different passes. These errors are calculated with respect to the real sensor poses, which were determined by manual measurements. However, it has to be noted that also these measurements are not exact, with regards to orientation. Consequently, the calibration errors are only given relatively with respect to this measurement. Although these calibrations only draw samples, it becomes obvious that due to the limited accuracy of the sensors more than the minimum number of source locations is necessary to obtain a sufficient calibration result. Furthermore, it is shown that redundant source locations improve the mean accuracy, whereas the improvements above 21 source locations are little.

	15 locations		**18 locations**		**21 locations**	
	MPF	**MOF**	**MPF**	**MOF**	**MPF**	**MOF**
1	24,7	4,0	34,2	2,8	28,6	2,3
2	37,8	3,3	53,6	5,0	28,7	2,9
3	45,3	5,2	31,2	3,5	36,1	2,4
4	46,6	6,3	21,7	2,3	46,4	3,6
5	81,2	8,9	45,6	4,5	24,6	2,8
Ø	47,1	5,5	37,3	3,6	32,9	2,8

Table III
Calibration results with 15, 18 and 21 source locations

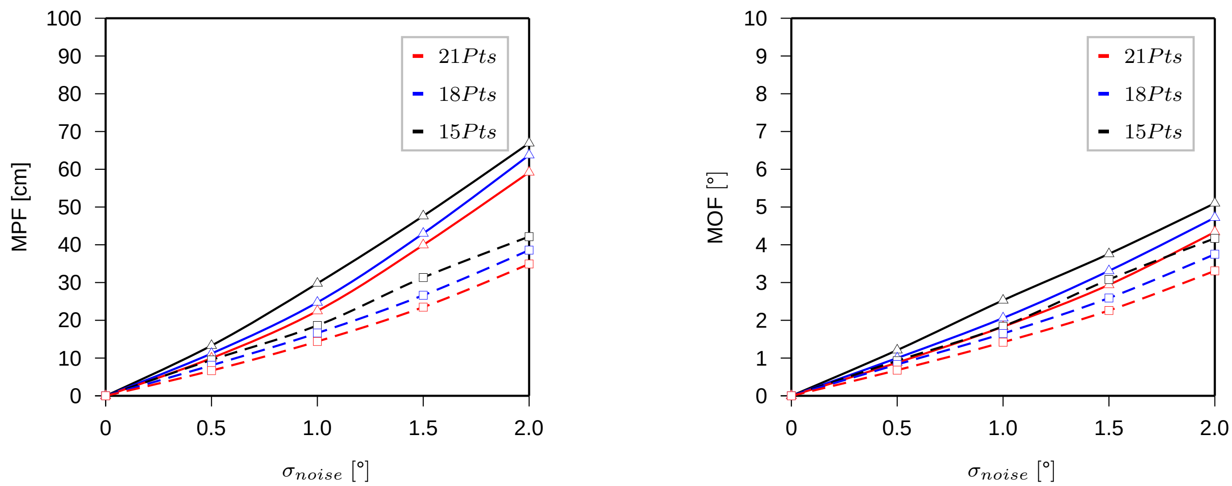
The actual benefit of the automated calibration are the tremendous time savings. In comparison to the manual calibration that required two people and lasted nearly two hours, the automated calibration could be carried out by one person in less than five minutes with 21 different source locations.

Finally, it should be noted that the calibration errors mainly depends on the accuracy of the used sensors and not on the proposed approach itself, as the simulation results show.

B. Simulation Results

As based on the real-world tests no general statement about the convergence, the accuracy and the behaviour under the influence of different noise levels can be given. We carried out several simulations, the results of which are presented in the following. For the simulations we applied the same setup as before. All simulations were done for 15, 18 and 21 different source locations, each with 1000 runs. The standard deviation of the measurement noise was adjusted in steps of 0.5° from 0.0° to 2.0°. According to former experiments, the AoA noise was modelled white and Gaussian. The source locations were generated randomly.

To evaluate the accuracy, only runs with a successful plausibility check were taken into account. In order to



(a) Mean position error

(b) Mean angle error

Figure 6. Calibration error with respect to noise

guarantee high convergence probability for these simulations (in contrast to the following ones), the initial guess was not randomly chosen but set to the exact sensor poses and source locations, whereas the latter were chosen non-deterministic. The resulting position and orientation errors are illustrated by the solid lines in Fig. 6(a) and 6(b). They confirm that an increased number of source locations improves the accuracy. Furthermore, the dependence between measurement noise and the mean position and orientation errors is shown to be almost proportional. As already mentioned, it is also clarified that the calibration accuracy only depends on the measurement error. If there is none, the calibration is exact. At this point, it should be clear that the position errors scale with room size whereas angular errors do not. This can be confirmed by comparing the results given in this paper with the formerly published one [1].

On the other hand, the results represented in dashed lines follow from simulations testing the convergence probability that will be described later on. The interesting aspect with respect to the former described simulations are the lower errors. The reason is easily explained: In the second simulation series random start values were used, which led to a lower overall convergence probability, especially for calibrations with more erroneous measurements. In conclusion, fewer bad results influence the mean values, which leads to lower mean errors.

As already mentioned, in the simulations used to determine the convergence probability, the initial guess was chosen randomly. The according outcomes are shown in Fig. 7. Dependent on the measurement noise the convergence probability lies between 0.38 and 0.21 for only one run per measurement set, whereas higher noise worsens the results as well as a higher number of source locations improves them. On the contrary, by increasing the number of tries per set up to ten, the probability rises to values between 0.92 and 0.67.

Finally, Fig. 8 illustrates the average number of runs for successful calibrations with a maximum of ten and the corresponding averaged computing time on a dual core PC with 3 GHz. It can be seen that typically three runs are required for a successful calibration, which takes between 2.5 and 6.6 seconds dependent on the number of source locations.

So finally it can be stated that the simulations confirm the measurement results. When comparing these results with the real world experiments, it can be assumed that the overall measurement errors lie between 1.5° and 2°, which equals the accuracy of the sensors. Additionally, it has to be noted that the convergence probability of the real measurements for 18 and 21 source locations is approximately 0.5 and thus lower than in the simulations. However, that may be founded due to the fact that the sensor model assumed in the simulations was quite simple as e. g. measurement errors due to partially seen objects were not considered.

VI. Conclusion

In this paper we presented a software-aided calibration approach for a triangulation-based indoor location system. This approach only requires that the user walks through the room and stops at random locations during calibration. Thereby, the localization of the nodes can be realized without any prior knowledge of sensor positions and orientations and the location of the moving person. Due to the limited computational power of the sensor nodes a centralized approach was chosen whereas the calibration problem is described by a non-linear system of equations. In order to solve this system, an enhanced Newton-Raphson method is applied, whereas unreliable measurements are identified and rejected

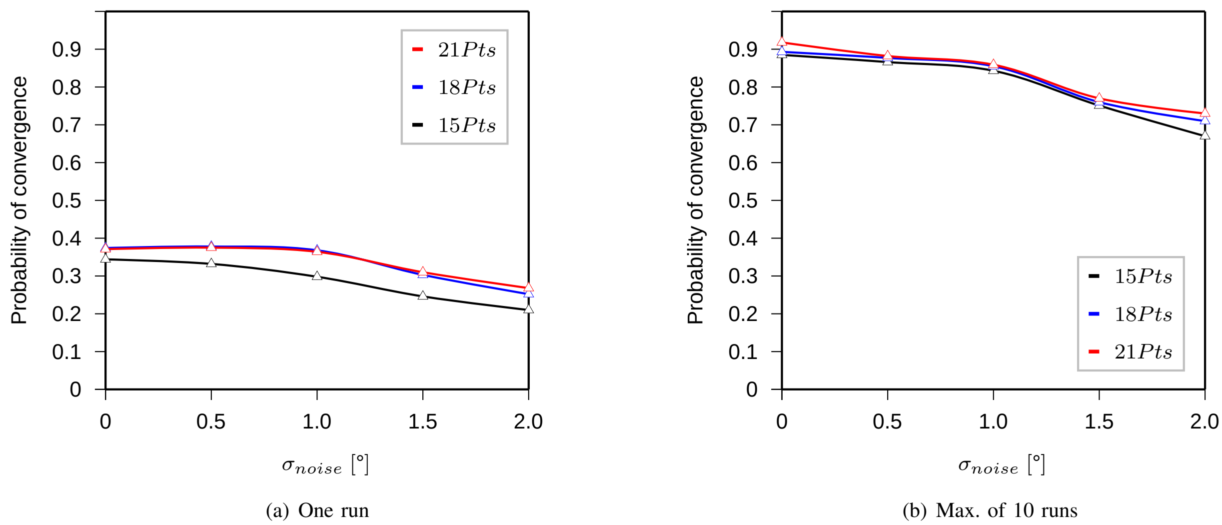


Figure 7. Probability of convergence with respect to the number of locations and measurement noise

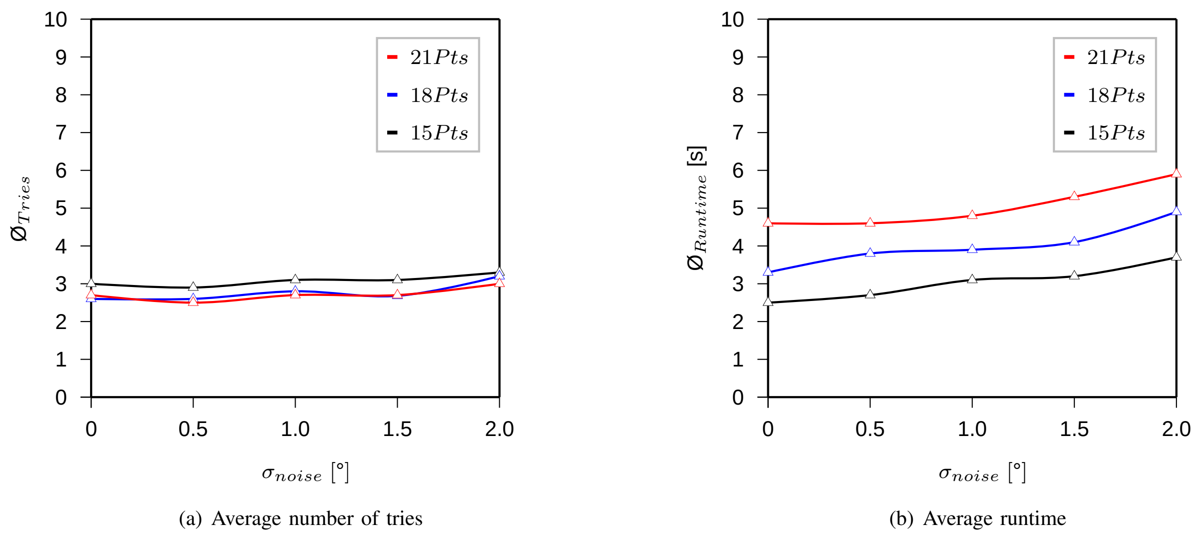


Figure 8. Average number of runs / runtime with respect to noise

based on a certain quality measure during a preselection process before the calculation is started. Real-world tests and simulations show that the algorithm works fine under the influence of noise and that an increased number of source locations improves the node localization accuracy. Furthermore, it could be illustrated that by the developed algorithm and software a calibration can typically be carried out in less than five minutes, whereas this time is dominated by the measurements. In comparison to a calibration based on manual measurement, which takes almost two hours, a significant improvement could be realized.

Future work will concentrate on improving the calibration results by developing movement strategies. Furthermore, strategies to improve the selection of the initial guess, like genetic algorithms, are examined. Additionally, the calibration software could be enhanced in a way that prior information, such as individual sensor positions can be manually fed into the algorithm in order to achieve better results.

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