



## Poster: NLOS-aware Localization Based on Phase Shift Measurements

Yannic Schröder and Georg von Zengen and Lars Wolf

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### Abstract:

Modern cars are already able to park in parking spaces adjacent to streets. Soon autonomous cars will be able to navigate themselves through parking garages to find a parking lot assigned to them. Indoor localization is essential to qualify cars and parking garages to perform this operation. Currently the reliability of many indoor localization schemes suffers from non-line-of-sight propagation paths. We present a position estimation algorithm for indoor localization systems based on phase measurements of electromagnetic signals. Our algorithm is designed to detect and exclude measurements originating from these non-line-of-sight paths to reduce their harmful influence on the localization.

# Poster: NLOS-aware Localization Based on Phase Shift Measurements

Yannic Schröder  
TU Braunschweig, IBR  
Mühlenpfordtstr. 23  
38106 Braunschweig,  
Germany  
schroeder@ibr.cs.tu-  
bs.de

Georg von Zengen  
TU Braunschweig, IBR  
Mühlenpfordtstr. 23  
38106 Braunschweig,  
Germany  
vonzengen@ibr.cs.tu-  
bs.de

Lars Wolf  
TU Braunschweig, IBR  
Mühlenpfordtstr. 23  
38106 Braunschweig,  
Germany  
wolf@ibr.cs.tu-bs.de

## ABSTRACT

Modern cars are already able to park in parking spaces adjacent to streets. Soon autonomous cars will be able to navigate themselves through parking garages to find a parking lot assigned to them. Indoor localization is essential to qualify cars and parking garages to perform this operation. Currently the reliability of many indoor localization schemes suffers from non-line-of-sight propagation paths. We present a position estimation algorithm for indoor localization systems based on phase measurements of electromagnetic signals. Our algorithm is designed to detect and exclude measurements originating from these non-line-of-sight paths to reduce their harmful influence on the localization.

## 1. INTRODUCTION

In future parking garages cars will drive autonomously from a drop-off point to their designated parking lot and back. During parking times electric cars may drive to special lots with charging capabilities and back to normal lots when fully charged to allow other autonomous cars to charge their batteries as well [9, 5]. For autonomous driving operations inside the parking garage the car needs to know its own position for navigation. Further, the parking garage must be aware of the position of all cars present to distinguish empty from occupied lots. In parking garages Global Positioning System (GPS) is not accurate enough to serve the needs of the described application. Also it can be unavailable due to attenuation of the signal by structural elements.

Further, indoor localization can be useful when guiding customers through a shopping mall. In this scenario small shops connected to a big hallway will result in many Non-Line-Of-Sight (NLOS) connections between fixed reference nodes with known positions (anchors) and mobile nodes (tags) carried by customers.

Therefore, we present an indoor localization system to overcome the disadvantages of GPS. Unlike other indoor

localization solutions our system is optimized to detect and handle often challenging NLOS measurements.

Our system utilizes phase difference measurements to determine the distance between nodes [2]. In this work we concentrate on how to estimate the position of a tag after measuring its distance to multiple anchors.

Other systems include NLOS measurements in their calculations by accounting for possible distance offsets and higher errors [6]. Phase measurements of NLOS connections cannot be included into distance estimations due to unpredictable reflections and refractions in different materials.

The proposed algorithm was tested in the Microsoft Indoor Localization Competition 2015 [1]. The system ranked 9th out of 23 competitors with an average distance error of 1.63 meters over 20 tested locations.

After giving a short overview of related work in Section 2 we present our map based approach to detect and mitigate NLOS measurements in Section 3. Afterwards, we describe the evaluation at the competition in Section 4.

## 2. RELATED WORK

Many indoor localization systems are prone to harmful influences of NLOS conditions. Especially in radio-based approaches the exact propagation path is often unknown resulting in wrong distance measurements and ultimately in wrong position estimates [8, 4].

Jung et al. detect NLOS conditions by using a known map of the environment for Time of Arrival (ToA) measurements in Ultra Wide Band (UWB) networks [6]. In ToA approaches the propagation path is critical as reflections prolong the time of flight and therefore the measured distance.

The algorithm proposed by Sathyan et al. returns multiple solutions from a ToA measurement [7]. Thereby the probability of the Line-Of-Sight (LOS) measurement being among the results increases. However, this approach fails when no LOS is available and all results are based on NLOS paths.

## 3. NLOS-AWARE APPROACH

The proposed algorithm is designed to localize a mobile node even in challenging environments like parking garages. It is based on measured distances to deployed anchor nodes.

Distances are calculated from phase shift measurements of a radio signal. The measurement is done by the Atmel Ranging Toolbox (RTB) [2]. This software is designed

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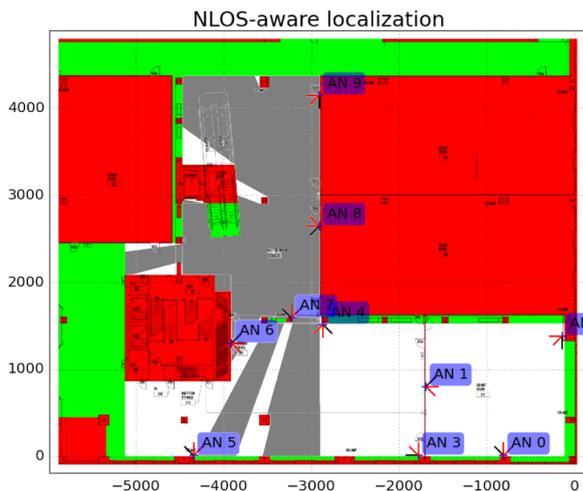


Figure 1: Output of our software with shadow map of anchor AN 8 (gray area). Both axes in cm

to use the Phase Difference Measurement Unit (PMU) of the IEEE 802.15.4 radio transceiver AT86RF233. The RTB reports a measured distance and a Distance Quality Factor (DQF). The DQF indicates the quality of the measurement and can be used to classify good and bad measurements by applying a cut-off value. Measurements may be bad if the radio channel is disturbed by other services like IEEE 802.11. Phase measurements are prone to errors due to NLOS-conditions. If the electromagnetic wave is reflected at a surface or refracted while passing through an object its phase is shifted. A reflection results in a phase shift of  $180^\circ$  while a refraction results in an unknown phase shift that depends on the refractive index of the object. Both phenomena can occur simultaneously resulting in unpredictable phase shifts.

Our localization algorithm uses a known 2D map of the deployment area to detect NLOS-conditions and impossible locations for the mobile node. We use a grid based approach comparable to a particle filter with particles aligned on a fixed grid. The grid can be represented as a matrix  $M$  enabling the use of optimized math libraries for computing the solution. Each element in this matrix represents a square cell in the deployment area. The size of  $M$  can be configured based on the needed accuracy and available computational capabilities. The 2D map of the environment is represented by a second matrix  $E$  of the same size as  $M$ . Each element of  $E$  indicates one of two special conditions for this cell of the environment:

**NLOS obstacle:** No LOS is possible through this cell and the mobile node cannot be located here (red areas in Figure 1). This condition is used to indicate walls.

**Positioning blocked:** A LOS is possible but the mobile node cannot be positioned here (green areas in Figure 1). This condition is used for restricted areas like atriums. In a parking garage this would indicate sidewalks or staircases as these are invalid locations for a car.

Shadow maps  $S_i$  are computed for each anchor  $a_i$ . Each shadow map is a boolean matrix that indicates LOS of all cells to the anchor node. Figure 1 shows the shadow map as an overlay (gray area) over the deployment area.

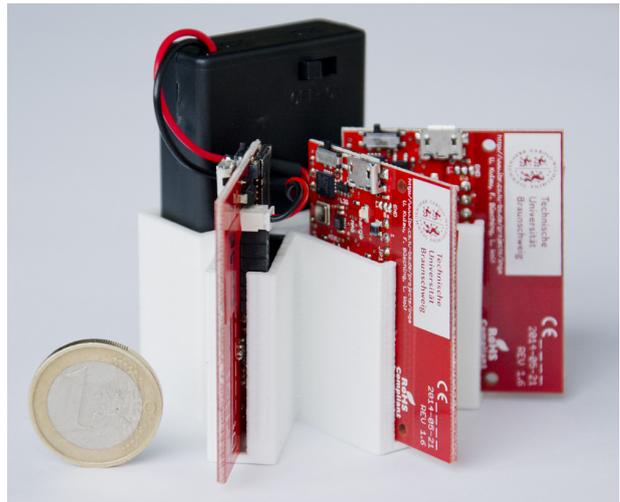


Figure 2: Anchor node consisting of three INGA sensor nodes with a coin for scale

Our battery powered anchor nodes consist of three INGA sensor nodes [3] and therefore feature three directional antennas, see Figure 2. The predominant directions of the antennas are  $22.5^\circ$  apart. Thus we can divide the area covered by each anchor node into three sectors. A distance value is measured for every sector individually.

The algorithm computes a probability for each cell that the mobile node is located in it. To do this, for each anchor a temporary matrix  $T_i$  is allocated. For each antenna sector an arc is drawn at the measured distance between the anchor and the mobile node. By using arcs and sectors we can reduce ambiguities that would arise when using full circles to mark possible locations. Drawn arcs can be configured to represent a specific probability distribution of distance measurements in the deployment area. Each arc is further weighted with the reported DQF of the measurement as a higher value indicates a better measurement result. The shadow map  $S_i$  is now used to remove impossible measurements for anchor  $a_i$ . The probability of every cell in  $T_i$  marked as NLOS in  $S_i$  is set to 0.  $T_i$  now contains the probabilities for the mobile node being in each cell based on the measurements from anchor  $a_i$ . The results in  $T_i$  are now added to the overall probabilities in  $M$ .

To find the most probable position for the mobile node the environment map  $E$  is taken into account. The probability of every cell in  $M$  not marked as normal cell in  $E$  is set to 0. By finding the maximum value in  $M$  the most probable location of the tag is computed. The indices of this cell in  $M$  correspond to the coordinates of the tags position in the deployment area. Figure 3 shows the final values of  $M$  color mapped as an overlay of the deployment area. In this example the tag is most likely located at the point  $(-3500, 2400)$  which translates to 35 and 24 meters, respectively.

## 4. EVALUATION

Our algorithm was tested in the Microsoft Indoor Localization Competition [1]. The evaluation area had a size of roughly  $2000 m^2$  ( $50 \times 40$  m) and consisted of an empty room and a big hallway with features like structural columns, beams, escalators and a staircase resulting in many NLOS

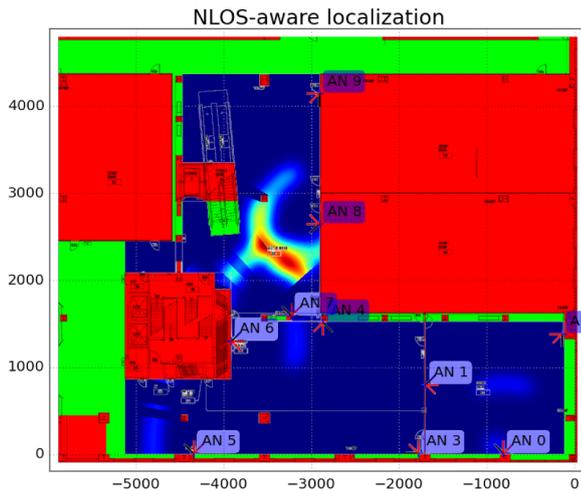


Figure 3: Relative probabilities of a tag’s position in the deployment area. Both axes in cm

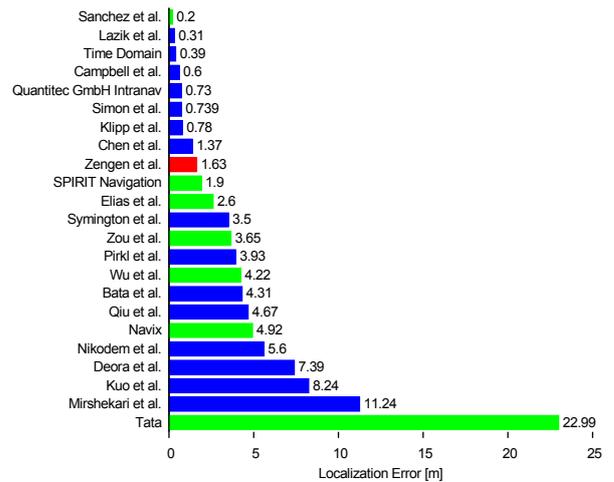


Figure 4: Official results of the Microsoft Indoor Localization Competition 2015, reproduced from [1].

connections (see Figure 1). The area was not empty during measurements, but conference attendees and other competing teams were using the space as well. However, other systems were turned off during the evaluation.

The competing systems were categorized by their need for additional infrastructure. Every contestant that deployed extra hardware was categorized as infrastructure-based and was allowed to deploy 10 units. As we deployed anchor nodes our system was infrastructure-based. All other systems were infrastructure-free and were only allowed to use a mobile device for localization. However, the supplied conference WLAN could be used as reference.

As a CAD file of the evaluation area was available prior to the event we were able to generate the needed map of the environment  $E$  beforehand. Only small adjustments were needed at the venue due to inaccuracies in the provided file.

The evaluation consisted of two days. On the first day all teams were allowed to set up their systems during a 7 hour time window. On the second day 20 previously unknown positions were marked down in the area. Each team had to locate every point and report its measured position to the referee. From these measurements the average distance error was calculated for each team.

Figure 4 shows the official results of the competition with infrastructure-free submissions marked in green. Our system (red) achieved an average distance error of 1.63 meters.

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