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IMPACT OF ANTENNA ORIENTATION ON LOCALIZATION ACCURACY USING RSSI-BASED TRILATERATION

[1,2]Dominik Csík, [1]Ákos Odry, [1,2]Richard Pesti, [1]Peter Sarcevic

[1]Department of Mechatronics and Automation, University of Szeged, Moszkvai krt. 9. 6725 Szeged, Hungary
[2]Doctoral School of Applied Informatics and Applied Mathematics, Óbuda University, Bécsi street 96/B 1034 Budapest, Hungary
e-mail: csikd@mk.u-szeged.hu

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ABSTRACT

The goal of the indoor localization is to determine the position and orientation of people, devices, and mobile robots. With the rise of Industry 4.0, wireless communication technologies have emerged as a rapidly evolving and crucial area for achieving this goal. Various radiocommunication-based technologies, including Bluetooth, Bluetooth Low Energy (BLE), Wi-Fi, Ultra-Wideband (UWB), and ZigBee offer means to indirectly estimate distance. These methods leverage diverse principles such as time-based measurements, signal strength, and angle of arrival. Indoor positioning systems can be categorized into two approaches: distance-based and distance-independent techniques. The Free Space Path Loss (FSPL) model describes the connection between distance and Received Signal Strength Indicator (RSSI). The parameters within this model significantly impact distance estimation and localization accuracy. Therefore, a method that accurately characterizes the model is critical. This work proposes an orientation-based localization technique utilizing RSSI and trilateration. Measurements were conducted between two ESP32 units in various orientations to obtain optimal parameters for each specific scenario. To assess the effectiveness of this approach, two scenarios were evaluated: one considering orientation and another neglecting it. The results show that incorporating orientation information leads to significantly more accurate positioning compared to the orientation-agnostic approach.

Keywords: indoor localization, fingerprinting-based methods, received signal strength indicator, radicommunication-based technologies

1. INTRODUCTION

Indoor localization is becoming increasingly crucial in the era of automation, where precise determination of positions and movement trajectories of mobile robots, tools, and workpieces is essential. Unlike outdoors, GPS has limited utility indoors due to obstacles that disrupt signals between transmitters and receivers [1], [2], [3], [4]. Therefore, alternative technologies and methods are required for indoor positioning. The range of devices utilized for indoor positioning systems is remarkably diverse, tailored to specific applications and operational needs. Technologies employed include camera systems [5], voice-based systems, radio communication-based technologies [6], [7], inertial systems [6], optical systems [3], and magnetic field monitoring systems [8], [9], [10]. The choice of technology depends heavily on the specific application requirements. Each technology thus offers its own set of advantages and limitations, influencing their adoption based on the precision, cost, and environmental conditions pertinent to the indoor localization task. Camera systems, while offering comprehensive coverage, tend to be more costly; they demand substantial lighting and considerable computational resources. Optical systems, on the other hand, provide high accuracy but also come with high costs due to the sophisticated equipment required [3]. Inertial systems, while useful for tracking relative positions, suffer from a significant drawback: their error tends to accumulate over time [9]. Consequently, they are less reliable for prolonged use without calibration or external correction methods. On the other hand, systems based on radio communication technologies are increasingly popular due to their scalability and versatility. These systems form wireless sensor networks (WSNs) wherein nodes communicate with each other and gather environmental data. The communication standards employed in radio communication-based systems are diverse, catering to various requirements of range, power consumption, and data transmission rates. Commonly used technologies include Bluetooth [6], WiFi [4], [7], [11], Bluetooth Low Energy (BLE), Ultra-Wideband (UWB) [12], ZigBee [13], and Z-Wave. WSNs are

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highly effective for determining positions and are commonly utilized in indoor environments where traditional GPS is ineffective. The methodologies employed within WSNs for positioning can be categorized into two broad groups:

- Range-based methods require measurements of distances or angles between the sensor nodes. Commonly used techniques include Time of Flight (TOF), Received Signal Strength Indicator (RSSI) [7], Time Difference of Arrival (TDOA) [3], and Angle of Arrival (AOA) [12]. Each of these techniques measures different aspects of the signals transmitted between nodes to calculate precise locations [13], [14].
- Range-free methods do not require precise measurement of distance or angles but rely on proximity or connectivity to estimate position. Fingerprinting techniques are a prime example, where the position is deduced by matching the observed signal characteristics to a pre-established database of signal patterns collected at known locations [7], [8], [13], [14].

Once distances or relative positions are ascertained using one of the above methods, a positioning algorithm is applied to compute the exact location. Common algorithms include trilateration [3], [15], [16], multilateration [15], and triangulation, each utilizing geometric principles to deduce position. This systematic approach allows for accurate indoor positioning across various applications, adapting to the specific requirements and constraints of the environment [13].

In this paper, a positioning method was proposed based on antenna orientation, utilizing trilateration to estimate positions. This approach harnesses the directional characteristics of antennas to improve the accuracy and reliability of position estimation. By measuring the distances from a target to at least three known points (antennas), and considering the orientation of each antenna, trilateration allows for the precise calculation of the position.

2. MATERIALS AND METHODS

2.1. Free Space Path Loss model

The Free Space Path Loss (FSPL) model is used to describe the propagation of radio signals through free space. This model is predicated on the principle that as a radio signal travels through space, it loses strength in a predictable manner. FSPL quantitatively expresses how the power of the radio signal decreases as a function of the distance between the transmitter and the receiver. The model can be expressed mathematically as (1):

$$FSPL[dB] = 20log_{10}(d) + 20log_{10}(f) + 20log_{10}\left(\frac{4\pi}{c}\right), \tag{1}$$

where d is the distance between the receiver and the transmitter, f the frequency of the signal and c is the speed of light.

Using this formula, the distance between two modules can be calculated by rearranging the formula to solve for d, assuming the other variables (such as f and the FSPL value) are known (2). This calculation is useful in systems where the signal strength can be measured, allowing the distance between transmitter and receiver to be estimated, facilitating applications like ranging and positioning.

$$d = 10^{-\left(\frac{RSSI+A}{10*N}\right)}, \tag{2}$$

where N is the path loss exponent, which reflects the rate at which the signal decays with distance. N typically ranges between 2 (in free space) and 4 (in environments with obstacles such as buildings or trees). A is the RSSI value measured at the reference distance (which is usually measured 1 meter from the transmitter).

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2.2. Particle Swarm Optimization

The 2 searched parameters, the A and N are determined using Particle Swarm Optimization (PSO). The optimization process begins by generating an initial population of particles. Each particle in this population is assigned a random fitness value to start. The movement of these particles is governed by their velocities, which are calculated based on a combination of influences that include the own best solution (cognitive component), the global best solution (social component), and its previous velocity (inertial component). During each iteration of the algorithm:

1. The velocity for each particle is updated by considering both the global best solution (the best solution found by any particle in the swarm) and the local best solution (the best solution found by particles) (3).

$$v_i(t+1) = \omega v_i(t) + y_1 u_1[p_i - x_i(t)] + y_2 u_2[g - x_i(t)], \tag{3}$$

   where ω is the inertial weight, $v_i(t)$ is the previous velocity of the ith particle, y_1 and y_2 are the social weights, u_1 and u_2 are random numbers, p_i is the best solution of the particle, $x_i(t)$ represents the previous position and g is the global best solution.
2. Using the newly calculated velocity, position of each particle is adjusted. This new position represents a potential solution to the optimization problem (4).

$$x_i(t+1) = x_i(t) + l v_i(t+1), \tag{4}$$

   where l is the learning weight.
3. The fitness value of each new position is evaluated to determine if it represents an improvement over previous solution.
4. If a particle finds a position that is better than any it has found before, it updates its personal best solution. Similarly, if a position is better than the global best found by the swarm, the global best is updated.

The algorithm continues to run until a termination condition is met, which could be a predefined number of iterations or a stagnation in fitness value improvement, indicating that further iterations are unlikely to produce better solutions. This method effectively searches the solution space by balancing the collective knowledge of the swarm (social influence) with individual particle experiences (cognitive influence), guided by the momentum of past movements (inertial influence) [11], [14].

2.3. Trilateration

Trilateration is a mathematical technique used for determining the precise position of an object based on the distances from multiple known points. It is widely used in various technologies, including GPS and indoor positioning systems. The initial step in trilateration is to measure the distance between the object (transmitter) and each of the reference points (receivers). These distances can be determined using methods such as RSSI or TOF. Each measured distance from a reference point defines the radius of a sphere. The center of each sphere is the position of its respective reference point (5).

$$(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2 = r_i^2, \tag{5}$$

where (x_i, y_i, z_i) represents the coordinates of the center of the spheres, and r_i is the radius.
The position is determined at the point where these spheres intersect. Due to noise and measurement inaccuracies, the spheres may not intersect at a single point perfectly. Methods like least squares are used to estimate the most probable position of the object, minimizing the total distance to the theoretical points of intersection [15], [16].

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2.4. Measurement system

The measurement system uses wireless technologies capable of measuring RSSI. The measurement system included 2 ESP32s, one of which was an AP, the other a STATION, which can be seen on Fig. 1. Data collection was carried out over a 4 meter section with multiple orientations at 20 cm intervals. At each point, 10 measurements were taken with every orientation, the average of the 10 measurement were used later. The position of the AP module remained fixed throughout, with its orientation changing every 90°. The STATION module moved along the designated path, and its orientation also changed every 45°.

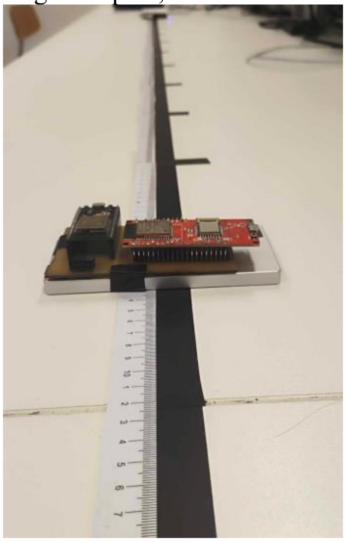

Figure 1. The STATION node during measurement

3. EXPERIMENTAL RESULTS

The results were evaluated in MATLAB environment. The objective function during the optimization was calculated using Mean Absolute Error (MAE) (6).

$$OF = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{d} - d\right|, \tag{5}$$

where n represents the number of measurement points, $\hat{d}$ is calculated distance and d is the real distance.

3.1. AP in fixed position examining directions separately

In the first case, the orientation of the modules had a prominent role. There were a total of 32 cases, which can be derivated from the 8 station and from the 4 AP orientation. The value of N was between 2.18 and 5.14, while the reference RSSI was varied between -66 dBm and -54.73 dBm. The smallest error was 20.63 cm, while the biggest error was 82.36 cm. The results can be seen in Tab. 1. RSSI-Distance functions for each Station directions can be seen in Fig. 2, when the AP orientation was 0°. Red line marks the optimized function, while the blue line marks the real, measured values.

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Table 1. Results for the case of AP in fixed position examining directions separately

Orientation		Orientation of AP											
		0°			90°			180°			270°		
		N	A [dBm]	E [cm]	N	A [dBm]	E [cm]	N	A [dBm]	E [cm]	N	A [dBm]	E [cm]
Orientation of Station	0°	4.09	-59.02	51.29	4.58	-55.44	43.57	3.95	-62.12	56.34	3.77	-60.01	46.10
	45°	5.14	-56.00	53.31	4.54	-54.73	56.02	4.34	-59.00	73.04	3.44	-61.63	49.72
	90°	3.50	-60.89	51.77	3.77	-62.01	54.52	4.20	-57.70	56.41	4.21	-60.58	52.38
	135°	3.66	-63.52	61.49	3.86	-63.74	67.60	3.88	-60.91	82.36	4.45	-59.52	69.38
	180°	2.18	-65.69	53.38	4.40	-60.76	52.45	4.80	-58.74	62.73	2.77	-66.00	61.36
	225°	4.20	-58.27	42.28	4.32	-58.00	47.15	4.49	-61.00	61.25	3.99	-60.86	45.40
	270°	4.06	-57.44	42.05	3.16	-63.06	51.72	3.40	-60.08	70.44	3.49	-61.00	49.22
	315°	4.32	-59.16	46.46	4.83	-57.97	56.13	2.79	-64.19	40.63	4.21	-60.57	63.01

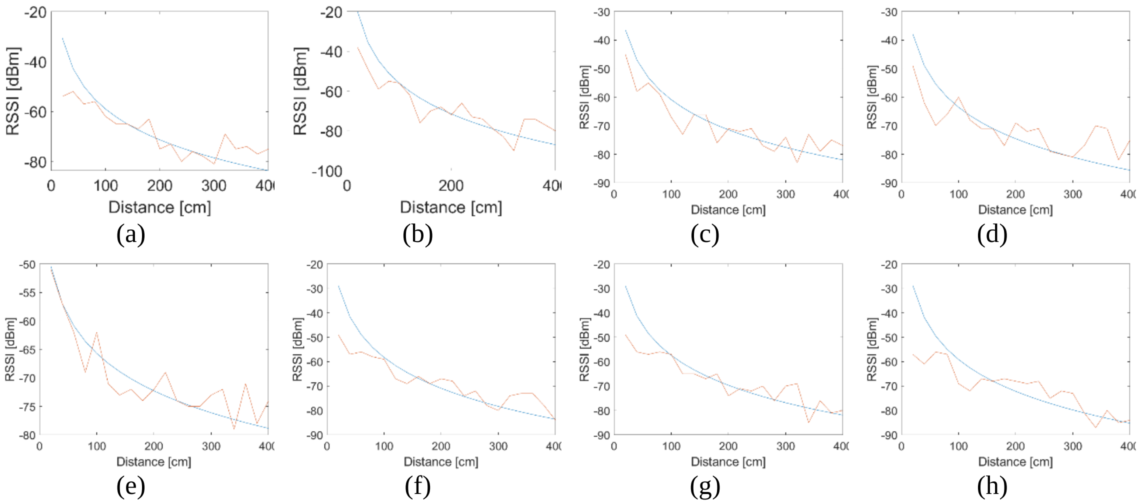

Figure 2. The FSPL model for different STATION orientations, when the orientation of AP was 0°, the orientation of the STATION was (a) 0° (b) 45° (c) 90° (d) 135° (e) 180° (f) 225° (g) 270° and (h) 315°

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3.2. AP in fixed position, angle has no effect

When the orientation was not considered, the N was 2.39 and the reference RSSI was –64.59 dBm. The smallest error was 54.16 cm, while the biggest error was 135.31 cm. The results can be seen in Tab. 2.

Table 2. Results for the case of AP in fixed position, angle has no effect

Orientation		N	A [dBm]	Orientation of AP			
				0°	90°	180°	270°
				E [cm]	E [cm]	E [cm]	E [cm]
Orientation of Station	0°	2.39	-64.59	69.66	77.23	97.51	58.17
	45°			103.46	86.10	103.34	55.30
	90°			65.83	102.49	74.85	88.76
	135°			85.38	113.89	90.23	91.41
	180°			54.16	126.63	94.89	81.07
	225°			61.10	88.51	119.84	88.91
	270°			69.21	66.54	77.89	64.46
	315°			104.66	135.31	56.04	89.70

3.3. Comparison of the cases

The comparison of the 2 cases can be seen in Tab. 3. The difference of the errors, and the improvement was determined. These values are positive if the first case, when the antenna orientation was considered, gave smaller errors than the other case. A significant improvement can be considered in the average of the MAE. Considering the orientation the average error had a value of 60.3 cm, while in the other case it had 85.7 cm. Considering the orientation gave better results in 28 cases from the 32 examined cases. The biggest improvement had a value of 77.34 cm, which is 57% relative improvement

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Table 3. Results for the case of AP in fixed position, angle has no effect

		Orientation of AP							
		0°		90°		180°		270°	
		Diffe-rence [cm]	Improve-ment [%]	Diffe-rence [cm]	Improve-ment [%]	Diffe-rence [cm]	Improve-ment [%]	Diffe rence [cm]	Improve-ment [%]
Orientation of Station	0°	10.64	15%	21.79	28%	35.38	36%	-1.85	-3%
	45°	47.46	46%	31.38	36%	44.34	43%	-6.33	-11%
	90°	4.94	8%	40.48	39%	17.16	23%	28.17	32%
	135°	21.85	26%	50.15	44%	29.32	32%	31.89	35%
	180°	-11.53	-21%	65.87	52%	36.15	38%	15.07	19%
	225°	2.83	5%	30.51	34%	58.84	49%	28.05	32%
	270°	11.77	17%	3.48	5%	17.81	23%	3.46	5%
	315°	45.50	43%	77.34	57%	-8.15	-15%	29.13	32%

4. CONCLUSIONS

This research introduced an orientation-focused optimization approach for assessing the environmental factor and reference RSSI in the FSPL model, using two different methods. The parameter optimization was conducted with the PSO algorithm. In the initial approach, the direction of the antenna was a key factor, whereas in the second method, data from all orientations were collectively used to set the parameters. The findings indicate that including the orientation enhances distance estimation substantially. This method enables an orientation-sensitive, RSSI-based distance measurement that could greatly enhance localization performance. Future objectives involve expanding measurements to more angles and using the trilateration technique for position calculations.

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