Study of Localization Algorithms of RFID Tags in Closed Areas

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Abstract: Nowadays, RFID technology is one of the most effective technologies used in identification. In addition to its role in identification efficiency and supply chain optimization, RFID technology is also widely used in the issue of accurate localization of objects in closed areas. With the help of RFID tags, devices can be identified in real time, data can be retrieved and stored remotely. Usually, RFID systems are used to search for moving objects in a certain area (indoors), control access, and monitor events. For example, the localization of RFID tags is one of the most important problems in tracking animals in farms, tracking assets in warehouses, and tracking patients in hospitals. Complex localization algorithms are the basis of this technological process. The article explores the algorithms used in the localization of RFID tags in closed areas through a careful study of principles, methodologies and existing applications

Key words:

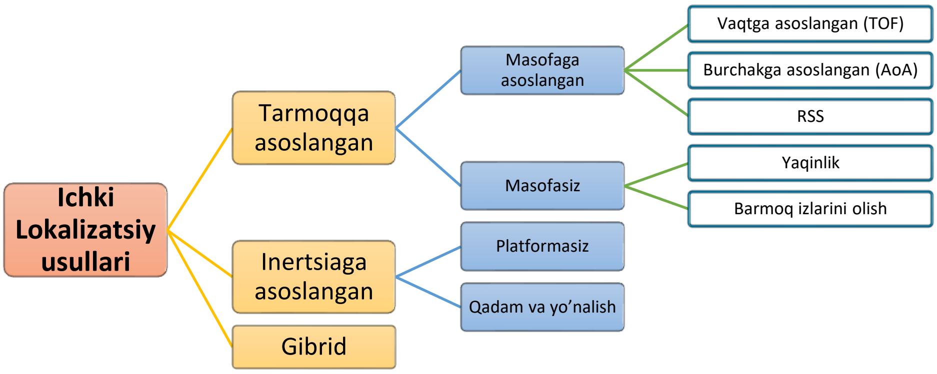
1. Introduction

Nowadays, RFID technology is one of the most effective technologies used in identification. In addition to its role in identification efficiency and supply chain optimization, RFID technology is also widely used in the issue of accurate localization of objects in closed areas. With the help of RFID tags, devices can be identified in real time, data can be retrieved and stored remotely. Usually, RFID systems are used to search for moving objects in a certain area (indoors), control access, and monitor events. For example, the localization of RFID tags is one of the most important problems in tracking animals in farms, tracking assets in warehouses, and tracking patients in hospitals. Complex localization algorithms are the basis of this technological process. The article explores the algorithms used in the localization of RFID tags in closed areas through a careful study of principles, methodologies and existing applications.

2. The basis of internal localization systems

Currently, Global Navigation Satellite Systems (GNSS) are an effective solution for tracking and localizing the position of an object in the external environment. However, there is no standard localization system that can be used in indoor environments around the world. Indoor positioning systems (IPS - Indoor Positioning Systems) are designed to provide information about the location of an object inside a building. The evolution of IPS helps to create Indoor Location Based Services (ILBS). Such services include locating products in a warehouse, tracking equipment in a hospital, guiding firefighters inside buildings that are difficult to see due to smoke, or assistive systems for elderly care. According to statistics, the estimated market value of closed localization services in 2020 was 10 billion dollars [1]. Therefore, there is a growing demand to develop IPS that can be popularized, expanded, and deployed in many buildings. There are three main requirements for IPS: (i) the system can accurately estimate the location of the object; (ii) the system is easily expandable; and (iii) the system infrastructure should be affordable. IPS systems can be divided into three groups (Figure 1): network-based systems, inertial systems and hybrid systems [6].

ISSN NO: 2770-4491
Date of Publication:11-10-2023

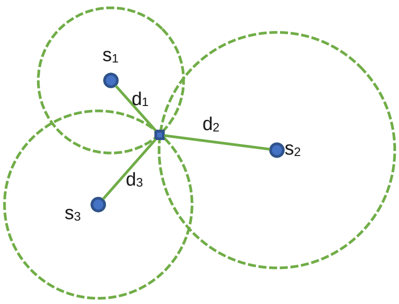


1-rasm. IPS tizimlari tasnifi.

According to the information obtained from wireless signals in the indoor environment, we can divide network-based IPS systems into two groups: distance-based and distance-free methods.

Distance-based methods extract geometric information (distance or angle) from the signals of different base nodes in a wireless network and combine the geometric information of each base node to obtain its position. There are various methods for obtaining geometric information from wireless signals, the most common being methods based on signal propagation time, angle of arrival (AoA) between transmitter and receiver, or received signal strength (RSS).

Time-of-Flight (ToF) localization methods measure the propagation time of a signal between a transmitter and a receiver. The distance between the target and the node is calculated by d=Δtv, where Δt is the propagation time of the signal and v is the propagation velocity. The simplest approach is called ToA Time of Arrival. In this case, the transmitter's radio packet signal transmission time is calculated by the receiver's reception time. If the distance to several base nodes is known, the target location can be obtained using the lateral method. Lateral methods (Figure 2) calculate the target location through the intersection of three circles. In the center of these circles, the base nodes are located, and the radius is equal to the calculated distance. In the ToA method, time synchronization is required between all nodes. The time difference of arrival (TDoA - Time Difference of Arrival) method is an alternative option that facilitates synchronization



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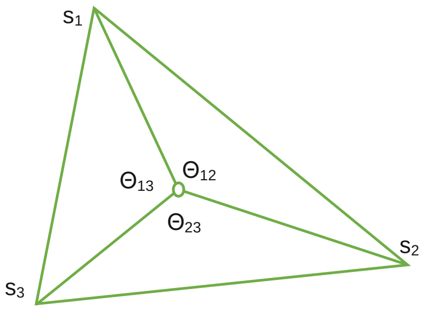

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Angle-based AoA (Angle of Arrival) localization methods use angles of signal arrival. After estimating the AoA, the calculation of the target location is done using triangulation. If the vertices of a triangle are known, the position of any node inside the triangle can be calculated.

RSS-based localization methods estimate the distance between target and base nodes using the received signal strength. These methods are based on the concept that the attenuation of the signal transmitted from the transmitter to the receiver depends on the distance. Distance estimation is modeled using a propagation model in a wireless environment. Typically, a logarithmic distance path loss model is used, where the attenuation (in dB) is proportional to the logarithm of the distance traveled: RSS=P_1m-10a log_10⁡d 10d-g, where d is the distance between the receiver and the transmitter distance, P_1m is the corresponding power measured at a distance of 1 m from the transmitter, α is the path loss index, and γ~N(0,s_g^2) models the shadowing effects. A small calibration is performed in each scenario to obtain the parameters P_1m and α of the model. The calibration process consists of collecting RSS with a certain distance to the reference point at predetermined positions and calculating the model parameters, which is usually done using regression methods. After calibration, the distance is estimated using the maximum likelihood estimator (MLE) according to the path loss model: d ̂=10^((RSS-P_1m)/190a).

ISSN NO: 2770-4491
Date of Publication:11-10-2023

Non-distance-based methods rely on inter-node connectivity information or location-dependent signal feature detection. Distance-free methods are based on wireless network connectivity information and are used for position estimation without distance measurements to the base node. It mainly has two types of algorithms: proximity and fingerprinting methods.

Proximity methods: use connectivity information to directly locate the target based on the number of neighboring base nodes. If the target is receiving a signal from the base node, then the target location is close to the base node. It scans radio signals from target base nodes. After the base node is detected, the target location is evaluated as the base node location. If several radio signals are detected, the base node with the strongest received signal is selected.

Fingerprinting methods: based on location-dependent factors of signals received from a wireless network. In the first step, a database of factors and the actual location where they are measured is collected. In the next step, the position is evaluated by selecting the position of the database sample that best matches the actual data.

Inertial systems calculate the position of a sensor object without physical infrastructure. In this case, the forces acting on the sensor are measured and the movement of the object on which the sensor is installed is considered. Inertial sensors consist of a 3-axis accelerometer, a 3-axis gyroscope, and a 3-axis magnetometer, forming an inertial measurement unit (IMU). There are two main types of inertial navigation systems:

Strapdown systems: these systems combine two-way target acceleration for location estimation.

Step and direction systems (SHS): these systems estimate the position of an object by adding initial position estimation vectors representing the step length and step direction of the object.

3. Passive (Backscatter) RFID system working principle

Most tags in RFID technology are based on passive tags. A passive tag receives power from the rider antenna signal and responds based on that power. That's why such systems are called passive backscatter (backscatter) RFID systems. Backscatter systems include an RFID reader and a passive tag (Figure 1). A passive tag consists of an antenna and a special integrated circuit chip, both of which have complex impedances (Zin and ZL). The chip receives power and data from the radio frequency (RF) signal transmitted by the RFID reader. The tag input impedance switches between two states (Zc1 and Zc2) and returns data by modulating the feedback signal. For each impedance state, the tag provides a specific RCS (Radar Cross-Section). Impedance states typically provide a high (RCS1) and low (RCS2) backscatter signal. Correct impedance matching between the antenna and the chip is also critical in passive RFID systems, as both power and frequency variations in chip impedance affect tag performance. This affects readability [5].

It can use different modulation and coding schemes for data exchange between the reader and the tag. The signal transmitted through the upper channel (uplink) (from rider to tag) includes continuous wave (CW-continuous wave) and modulated commands. Bottom line al (downlink) (tag-to-rider) data is returned during one of the CW cycles when the tag impedance modulates the return signal. Now the transmission model of passive RFID systems and the calculation of reading distance are considered.

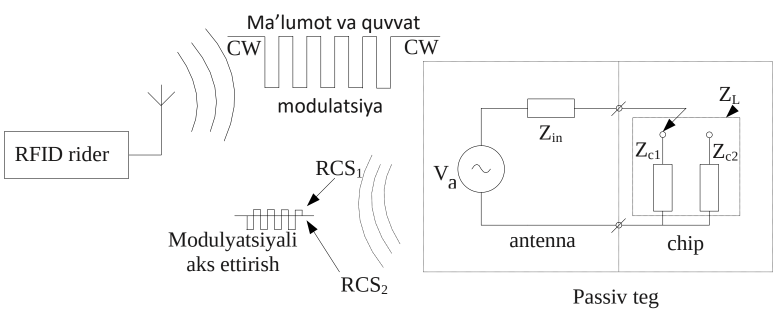


Figure 1: Passive backscatter RFID system.

In passive tag RFID systems, the operating power required by the tag is transmitted from the rider. It depends on the overall performance of the radio communication between the rider and the tag. The characteristics of the reader or tag, such as transmission power, antenna power, operating frequency, radar area, quality factor, effective aperture or scattering aperture, polarization and receiver sensitivity are considered as the main factors affecting the reading distance.

Transmission model based on the upper channel (Uplink). According to Fries open-space transmission equations, the power received at the reading distance R can be calculated by formula (1).

$$P_r(R) = \frac{P_t G_t(\theta_t,\varphi_t) G_r(\theta_r,\varphi_r)\lambda^2}{(4\pi)^2 R^2 L} \qquad (1)$$

where P_r (R) is the reception power of the receiving antenna, R is the distance between the receiver and the transmitter, G_t (θ_t,φ_t) the power of the transmitting antenna, G_r (θ_r,φ_r) the power of the receiving antenna, λ is the wavelength, P_t is the power transmitted by the transmitting antenna, L is the loss factor of the system (L=1 indicates no loss in the system hardware).

In passive RFID systems, the upper channel is rider-to-tag transmission. Rider-transmitter, tag-receiver. Where (G_t) is the tag with the rider's maximum power direction, and (G_r) the tag's maximum power direction is the same as the rider. At the same time, it is assumed that the direction of polarization of the rider is the same as that of the tag. This can be shown by (2).

$$P_r(R) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 R^2} \qquad (2)$$

Downlink transmission model. According to the open space radar transmission equations, the signal strength received by the tag is proportional to the propagation area.

$$P_i = \sigma S_i \qquad (3)$$

where σ is the captured power of the tag, P_i is the scattering area, S_i is the power density falling from the tag.

When the incident power is uniformly distributed:

$$S_s = \frac{P_i}{4\pi R^2} \qquad (4)$$

S_s *is the transmission power density of the receiving radar antenna. From* (3) *and* (4).

$$\sigma = 4\pi R^2 \frac{S_s}{S_i} = 4\pi R^2 \left|\frac{E_s}{E_i}\right|^2 \qquad (5)$$

where E_s is the intensity of the electric field going to the tag, E_i is the electric field strength of the radar antenna radiating from the tag, and s is the measurement of the propagation of the tag electromagnetic field in the direction of the radar receiving antenna.

Thus, the power received by the radar can be expressed as follows

$$P_r = \frac{P_t G_t(\theta_t,\varphi_t) G_r(\theta_r,\varphi_r)\lambda^2\sigma}{(4\pi)^3 R_1^2 R_2^2} \qquad (6)$$

$R_2 -$ *the distance between the transmitting antenna and the tag*, R_1 $-$ *the distance between the receiving antenna and the tag (bistatic radar).* $G_t(\theta_t, \varphi_t)$ *is the transmitting radar power,* $G\_t\ (\theta\_t, \varphi\_t\ )$ *is the receiving radar power.*

For monostatic radar, G_t (θ_t,φ_t)=G_r (θ_r,φ_r), can be defined as P_r

$$P_r = \frac{P_t G_t(\theta_t,\varphi_t)^2 \lambda^2 \sigma}{(4\pi)^3 R^4} \qquad (7)$$

In passive backscatter RFID systems, the rider usually has a monostatic radar antenna, and the electric field polarization of the rider is the same as that of the tag, so the RFID rider's intercepted power (8) is obtained, which is defined as the RCS (radar cross section) model.

$$P_r = \frac{P_t G_t^2 \lambda^2 \sigma}{(4\pi)^3 R^4} \qquad (8)$$

Reading distance calculation. According to the upper channel transmission model, the received tag power is calculated by Equation (2). Assuming the initial power of the tag is P_min, the tag will start when P_r≥P_min. According to the sub-channel transmission model, the rider is activated when the signal reception power of the rider antenna from the tag is 〖P^'〗_r (R^')≥〖P'〗_min, where 〖P^'〗_r (R ^') is the minimum required rider power, 〖P'〗_min is the initial rider power.

In this $P_r = P_{min}$ (9)

ISSN NO: 2770-4491
Date of Publication:11-10-2023

$$P_{min} = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 R^2} \qquad (10)$$

Maksimal o'qish masofasi R_{max} sifatida olinishi mumkin

$$R_{max} = \frac{\lambda}{4\pi}\sqrt{\frac{P_t G_t G_r}{P_{min}}} \qquad (11)$$

Ochiq fazoda

$$S_i = \frac{E^2}{2\mu_0}, \mu_0 = 120\pi \qquad (12)$$

$$R_{max} = \frac{\sqrt{60 P_t G_t}}{E_0} \qquad (13)$$

$$P'_r(R') = P'_{min} \qquad (14)$$

$$P'_{min} = \frac{P_t G_t^2 \lambda^2 \sigma}{(4\pi)^3 R'^4} \qquad (15)$$

Maksimal o'qish masofasi R'_{max} sifatida ifodalash mumkin

$$R'_{max} = \left[\frac{P_t G_t^2 \lambda^2 \sigma}{(4\pi)^3 P'_{min}}\right]^{\frac{1}{4}} \qquad (16)$$

Ochiq fazoda pastki kanal modelini hisobga olgan holda

$$R'_{max} = \frac{\lambda}{4\pi}\left[\frac{P_t G_t^2 G_r}{P'_{min}}\right]^{\frac{1}{4}} \qquad (17)$$

Passiv RFID tizimi ishlaganda, tizim maksimal o'qish masofasi sifatida olinishi mumkin

$$R'_{max} = \min\{R_{max}, R'_{max}\} \qquad (18)$$

4. Preliminary analysis of the localization area

A common distinguishing feature of a number of existing localization methods is a training phase for preliminary analysis of the localization area by collecting measurement information (O'A) at various points of the area (this phase is sometimes called scene analysis). In this case, the localization area is divided into U cells, and an RFID tag is placed in each cell. Then several (O times) measurements are made for each of the N antennas of the rider. The resulting measurements are stored in the data storage unit. Then a table (map) of the obtained data is created (such methods are called fingerprint methods). After the table is created, the coordinates of the placed tags are evaluated [3].

Most of the literature deals with RSS measurement information. As an example, the structure of the RSS table in the two-dimensional localization area is divided into U=4 cells, the number of measurements is O=2 and N=3 antennas (Table 1). Table cells RSS_(u,n,n) contain the RSS values obtained during measurements, where u is the cell number in the localization area, n is the antenna number, o is the measurement number.

Table 1. An example of an RSS fingerprint table structure

Yacheyka		RSS qiymatlari					
u	(*x*, *y*) koordinatalar	antenna *n*=1		antenna *n*=2		antenna *n*=3	
		o=1	*o*=2	*o*=1	*o*=2	*o*=1	*o*=2
1	(x_1, y_1)	$RSS_{1,1,1}$	$RSS_{1,1,2}$	$RSS_{1,2,1}$	$RSS_{1,2,2}$	$RSS_{1,3,1}$	$RSS_{1,3,2}$
2	(x_2, y_2)	$RSS_{2,1,1}$	$RSS_{2,1,2}$	$RSS_{2,2,1}$	$RSS_{2,2,2}$	$RSS_{2,3,1}$	$RSS_{2,3,2}$
3	(x_3, y_3)	$RSS_{3,1,1}$	$RSS_{3,1,2}$	$RSS_{3,2,1}$	$RSS_{3,2,2}$	$RSS_{3,3,1}$	$RSS_{3,3,2}$
4	(x_4, y_4)	$RSS_{4,1,1}$	$RSS_{4,1,2}$	$RSS_{4,2,1}$	$RSS_{4,2,2}$	$RSS_{4,3,1}$	$RSS_{4,3,2}$

In the initial analysis of the localization area, the localization group includes several methods. Now the most popular of them are nearest neighbor, artificial neural networks and support vector machine methods.

The nearest neighbor method implements the following algorithm:

initial analysis stage: an RSS table is created in the localization field;

RSS values are obtained from each tag through all antennas in the system (a vector ω is generated from the RSS values);

vector ω is compared with each RSS_u in the RSS table, searching for the minimum difference (or maximum similarity) between RSS_u and ω;

the coordinates of the found row will be the coordinates of the tag λ=(x ,y ̂).

ISSN NO: 2770-4491
Date of Publication:11-10-2023

In the algorithm, a search for a nearest neighbor is performed in the vector space of RSS values. Calculation of tag coordinates using the minimum difference criterion is as follows:

$$\hat{l} = position\left[\arg\min_{u\in\{1,\ldots U\}} \Delta(\omega, RSS_u)\right], \qquad (1.2)$$

where position(u) is a function to get the coordinates of the localization area cell by number u; Δ(ω,RSS_u) is the difference function between vector ω and vector RSS_u.

The function Δ(ω,RSS_u) is determined by the method of least squares:

$$\Delta(\omega, RSS_u) = \sum_{n=1}^{N}\left(\omega_n - \frac{1}{O}\sum_{o=1}^{O} RSS_{u,n,o}\right)^2. \qquad (1.3)$$

K nearest neighbors (kNN) method and K weighted nearest neighbors (kmNN) method. In the implementation of these methods, not a single vector, but K vectors with minimum difference in the RSS space are searched. After that, the average coordinates of cells corresponding to the found vectors are calculated. Weighting coefficients are taken into account when averaging in the kmNN method. In this case, Δ(ω,RSS_u) is determined by the difference function values (1.3).

The k-nearest neighbor algorithm has been widely used in RFID tag localization problems in several research works. For example, Ahmad Fali and others effectively used the K-nearest neighbor algorithm in the localization of RFID tags in parking lots, and Muhammad Zikrillah and others in keeping the list of employees' attendance at work between RFID tags[9-10].

Artificial Neural Network (ANN). The ANN-based method consists in training the network on a sufficiently large sample of measurement data obtained at the initial analysis stage. If the training is successful, the ANN can predict the location of the tags. In this case, the resulting estimate can be constructed as an estimate of the location coordinates λ ̂of the tag (point approach) in each of the zones F or the probability vector of finding the tag π ̂. Zone F is a localization area (zone approach). The general algorithm of controlling the localization system based on ANN may look like this:

the initial analysis stage is performed in the localization area, a measurement table divided into two sub-tables of U_1 and U_2 lines is built;

ANN structure and ANN training algorithm are chosen;

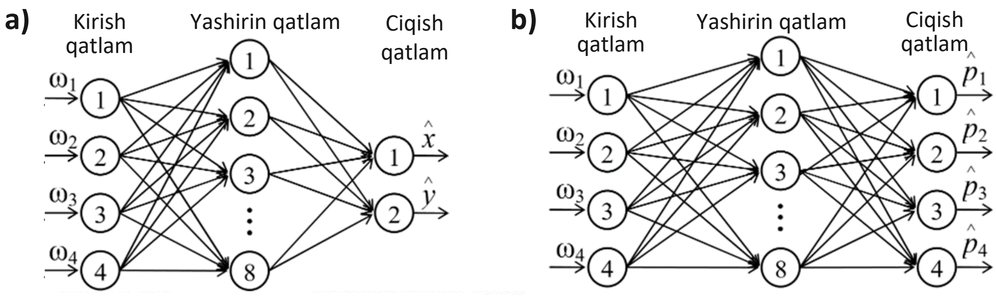
The ANN is trained on the first subtable data;

the trained ANN is tested using the data of the second sub-table and the consistency of the resulting ANN calculations is checked;

if the calculations do not correspond to the actual values, the structure of the ANN or the training algorithm is changed, then points 3 and 4 are repeated;

If the calculations correspond to the true values, the ANN is considered to be formed. The ANN calculation step begins, where after inputting the vector ω, the location of the labels is estimated.

Typically, multi-layer perceptrons with a single internal layer are used as ANNs for spatial localization. The number of input neurons is proportional to the number of antennas in the system, and the number of output neurons is equal to the spatial dimension (or number of zones) divided by the localization region. Backpropagation algorithm can be used in ANN training. Examples of three-layer perceptron schemes in the implementation of both variants of the localization method are shown in Figure 1.4 (numbers indicate the number of neurons in each layer). In this case, using 8 neurons in the hidden layer, the localization area is divided into F=4 zones and includes N=4 antennas.



ISSN NO: 2770-4491
Date of Publication:11-10-2023

Figure 1.4. Examples of artificial neural network schemes are: (a) determination of point coordinates in the location of RFID tags and (b) calculation of the probability vector of tag placement in areas divided into localization zones

Support Vector Machine (SVM). The SVM method is usually implemented using a classification algorithm. The essence of the SVM classification method is to search for several hyperplanes, each of which divides the N-dimensional space into two parts. In this case, each part of the measurement space is associated with a specific zone of the localization area.

If the classifying hyperplanes are found, then the vector ω of the system with N antennas can be successively classified in the dimension space using each of the hyperplanes. Since the parts of the measurement area correspond to the zones of the localization area, the result zone of the localization area is found at the time of classification, which is the approximate location of the tag.

The generalized algorithm of the SVM method is written as follows:

the stage of preliminary analysis of the localization area is carried out and a measurement table is drawn up, each place where measurements are taken is assigned to one of the F zones into which the localization area is divided;

SVM training is carried out by analyzing the measurement table (the required number of hyperplanes is determined and the parameters determining their location in the measurement space are formed);

At the next stage, a measurement vector ω is created during the localization of a certain tag;

The ω vector is classified in the measurement space using the generated hyperplanes, after which the localization area zone is determined, which is taken as an estimate of the location (or the vector of the probability of finding a symbol in each of the F zones is found).

Based on the preliminary analysis of the localization area, the considered methods allow to achieve a much higher accuracy of localization. In this case, the accuracy depends primarily on the size of the measuring table. For the ANN method, the accuracy depends significantly on the type and structure of the network, and for the SVM method, the accuracy depends on the training algorithm.

However, creating a scale table large enough to improve localization accuracy is time-consuming. In addition, due to changes in localization status, the collected data can quickly become outdated. Therefore, beacon tags are used to overcome these shortcomings.

In general, the methods of preliminary analysis of the localization area are as follows [7]:

1) Landmark - the system is based on the kNN method. Reference tags with known positions are placed in a permanent closed area. Riders have eight different power levels. This approach consists of selecting the k closest reference tags from the unknown active tag with indicator (4) for each j-reference tags. E represents the relationship between each reference tag and target tag. With (5), the coordinates of the k closest reference tags are used to identify the tag. The lowest E standard tag is the highest weight.

$$E_j = \sqrt{\sum_{i=1}^{n} \left(\theta_{j,i} - S_i\right)^2} \qquad (4)$$

$$(x_e, y_e) = \sum_{i=1}^{k} w_i (x_i, y_i),\ w_i = \frac{\frac{1}{E_i^2}}{\sum_{i=1}^{k} \frac{1}{E_i^2}} \qquad (5)$$

here, n is the number of riders; S_i – RSS value of target tag measured by i-rider, θ_(j,i) – RSS value of reference tag j measured by i-rider.

2) VIRE – always uses standard tags in a plane. This method introduces the concept of affinity mapping. The entire localization area is divided into small areas. The center of each region corresponds to a corresponding reference tag. Each rider maintains its own affinity map. If the difference between the RSS measurement of the unknown tag and the RSS measurement of the region is less than the threshold value, the region is marked as '1'. Combining all riders' maps gives a global affinity map for a tag. Two weighting coefficients are determined. The first (6) indicates that the RSS measurement between the selected reference tags and the target tag does not match. The second (7) weight coefficient is a function related to the density of selected reference tags. The densest region has the highest weight. As a result, the tag coordinates are calculated with (8):

$$w_{1i} = \sum_{j=1}^{n} \frac{\left|\theta_{j,i} - S_i\right|}{n \times \theta_{j,i}} \qquad (6)$$

$$w_{2i} = \frac{p_i}{\sum_{j=1}^{n_a} p_j} \quad (7)$$

$$(x_e, y_e) = \sum_{i=1}^{n_a} w_{1i} \times w_{2i}(x_i, y_i). \quad (8)$$

where n is the number of riders, S_i is the RSS value of the target tag measured from the i-rider, θ_(j,i) is the RSS value of the j-standard tag measured by the i-rider, n_a is the total number of regions; p_i is the ratio of conjunctive possible areas to the total area.
3) Simplex – based on placement of reference tags, this method requires n riders with K-level transmission power. To localize a tag, riders start at the lowest power level and increase their transmission power over time until they receive a response from the tag. At the same time, each rider will also receive feedback from Elalon tags. L_(i,j) is the distance between rider i and tag j. The distance L_(i,j) is found by averaging the distances of the riders to all reference tags detected at the same power level. By minimizing the error function, the location j is calculated as follows:

$$\epsilon_j = \sum_{i=1}^{n} \left(\frac{L_{i,j} - \hat{L}_{i,j}}{L_{i,j}}\right)^2. \quad (9)$$

The simplex method is used to minimize e_j.
4) Kalman filtering - also uses etalon tags. The first step is to calculate the distance D_i between each reference tag and the target tag using the RSS measurements of the two riders. The location of the tag is solved by the system of nonlinear equations with the minimum mean square error algorithm (10). The second step is to create a probability map to measure rider field error. The first step is applied to each benchmark label. The corresponding error probability distribution function is calculated using their estimated and actual locations. This map iteratively uses a Kalman filter to reduce the effect of RSS measurement error and improve localization accuracy.

$$(x_i - x_e)^2 + (y_i - y_e)^2 = D_i^2, \forall i = 1, \ldots n,$$

5) Scout - belongs to the family of probabilistic localization methods, which uses standard tags and several riders. Target tags are localized in three steps. 1) distribution parameters are calibrated using built-in reference tags. 2) the distance between the target tag and riders is determined using the RSS probability model. 3) tag location is determined using Bayesian inference. Repeated predicted proxies are calculated. Observations are then adjusted until a good model is obtained, resulting in an approximate field.

5. Multidimensional scaling (MDS-RFID) algorithm

Multidimensional Scaling (MDS - Multidimensional Scaling) is an effective solution for localization. Similarity scores in MDS correspond to Euclidean distances. MDS-based localization algorithm (MDS-MAP) has been well studied in wireless sensor networks. The MDS-MAP algorithm forms the distance matrix by first running the shortest path algorithm. MDS is then performed to determine the approximate sensor locations that best match these distance measurements. Finally, reference points are used to calculate absolute coordinates based on linear transformations and rotations. MDS-MAP is a popular localization algorithm in wireless sensor networks and has many variants [8].

In this case, RFID readers, which act as benchmarks, are placed in predetermined places. When taking each rider RSS measurement from RFID tags attached to objects, it is assumed that all riders are within the signal range of the tags. This can be simplified by dividing large networks into smaller networks. All RSS measurements are integrated into the server where the MDS-RFID localization algorithm is executed. The purpose of the localization algorithm is to determine the position of the RFID tags, taking into account all the RSS measurements in the system. The MDS-RFID algorithm consists of three steps: data preprocessing, multidimensional scaling (MDS), and refinement.

A. Data preprocessing step

In the first step of the MDS-RFID algorithm, a distance matrix is constructed to access the MDS. The data available in the system is the RSS measurements of all tags received from each rider. This step consists of two parts: determining the tag-to-rider distance using RSS measurements, and calculating the inter-tag distance based on this tag-rider distance data. The distance matrix between pairs (tags and riders) is then input to the stage.

ISSN NO: 2770-4491
Date of Publication:11-10-2023

1) RSS-Distance Model: To determine the distance between a transmitter (active tag) and a receiver (rider) via RSS, signal attenuation and path loss over distance must be modeled. For the indoor environment, the following logorphmic-normal distance path loss model is used [2]:

$$PL(d) = PL(d_0) + 10n\log\left(\frac{d}{d_0}\right) + z \qquad (1)$$

where PL(d) is a random variable describing the path loss (distance d is measured in dB), d_0 is the reference distance, n is the path loss index, and z is the random is a variable that follows an N(0,s^2) Gaussian distribution. The roadway index n is equal to 2 in an open environment and in the range of 2-4 in a closed environment. The standard deviation s in the model varies from 3 dB to 12 dB in closed environment [2].

Given the transmission power P_t, the transmitting antenna voltage G_t and the receiving antenna voltage G_r, the RSS at distance d can be obtained as P(d)

$$P(d) = P_t + G_r + G_t - PL(d) = c - 10n\log(d) - z \qquad (2)$$
$$c = P_t + G_r + G_t - PL(d_0) + 10nlog(d_0)$$

where c is a constant.

From (2), the RSS distance model can be obtained by estimating the distance d.d ̂(P)=10^((c-P)/10^n). (3)

In a real environment, due to multipath propagation and other factors, the RSS model may not fully follow. But experiments show that MDS is tolerant of such uncertainties.

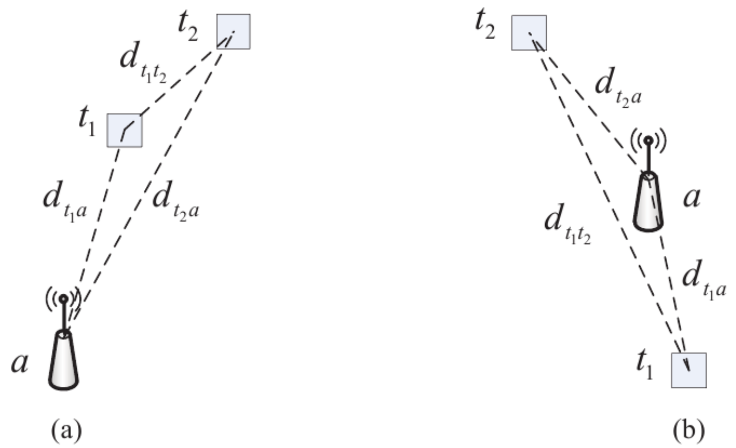
2) Estimating the distance between tags: Let A be a set of riders and T be a set of active tags, let d_ta be the distance from tag t∈T to a∈A rider. Given the RSS measure P_ta, d_ta can be estimated using (3). $\hat{d}_{ta} = 10^{\frac{c-P_{ta}}{10^n}}$. (4)

However, this method is not useful for distance calculation when a tag cannot connect to another tag. In order to solve this problem, a triangular method using two tags t_i,t_j and a rider is proposed to estimate the distance between tags t_i and t_j. Given the distance d_(t_i a) and d_(t_j a) from the tags to the rider, the upper and lower limits of the distance d_(t_i t_j) between the tags are obtained using triangular inequalities.

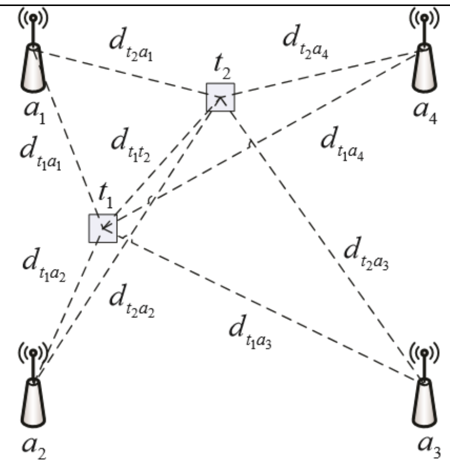
$$\left|d_{t_ia} - d_{t_ja}\right| \le d_{t_it_j} \le d_{t_ia} + d_{t_ja}. \qquad (5)$$

The lower and upper limits of the inter-label distance are shown in Figure 1. Two t_1,t_2 tags and one a rider are placed. In this case, when two tags are placed on one side of the rider, the distance between the tags d_(t_1 t_2) is the lower limit$\left|d_{t_1a} - d_{t_2a}\right|$ is calculated with The upper limit of the distance between t_1 and t_2 corresponds to the case where the rider lies between the tags.

When there are more riders in the system, the limits of the inter-tag distance become clear, because more triangles created by two tags and riders can be used. Then the inter-label distance can be calculated using all riders with a maximum lower limit and a minimum upper limit (5).



1-rasm. (a) t_1 va t_2 teglar a riderning bir tomonida bo'lgan holat, quyi chegara $d_{t_1t_2}$; (b) t_1 va t_2 teglar a riderning o'rtasidagi holat, yuqori chegara $d_{t_1t_2}$.



2-rasm. Riderlar maydonning burchaklariga joylashtirilgan holda teglararo $d_{t_1t_2}$ masofani baholash

Currently, the distance between tags is calculated only by d_ta from tag to rider. If the measurement differences dˆ_ta are taken into account, the average calculation of the limits given by the triangle method using all riders of the inter-label distance gives a better result:

ISSN NO: 2770-4491
Date of Publication:11-10-2023

$$d^{l}_{t_i t_j} = \frac{\sum_{a\in\mathcal{A}}\left(\left|d_{t_i a} - d_{t_j a}\right|\right)}{|\mathcal{A}|} \tag{6}$$

va

$$d^{u}_{t_i t_j} = \frac{\sum_{a\in\mathcal{A}}\left(\left|d_{t_i a} + d_{t_j a}\right|\right)}{|\mathcal{A}|}, \tag{7}$$

bu yerda $d^{l}_{t_i t_j}$va $d^{u}_{t_i t_j}$ - teglar orasidagi $d_{t_i t_j}$ masofaning quyi va yuqori chegarasi bo‘lib, tegdan ridergacha bo‘lgan taxminiy masofa; $|\mathcal{A}|$ - riderlar soni.

Riderlarni maydonining burchaklariga joylashtirilganda, ular teglar o'rtasida yotishi mumkin emas (2-rasm). Bunday holda, teglararo masofa uchun faqat quyi chegara samarali va $d_{t_i t_j}$ masofa quyi chegara bilan hisoblanadi: $\hat{d}_{t_i t_j} = d^{l}_{t_i t_j}$. Agar riderlar tasodifiy joylashtirilsa, $d_{t_i t_j}$ masofa $\hat{d}_{t_i t_j} = \left(d^{l}_{t_i t_j} + d^{u}_{t_i t_j}\right)/2$ deb hisoblanadi, chunki qaysi chegara samaraliroq ekanligi noma'lum.

To'rtta rider a_1, a_2, a_3, a_4 maydonning burchaklariga va ikki t_1, t_2 teg maydon ichiga joylashtirilgan. Barcha tegdan riderlargacha masofalardan t_1 va t_2 teglar orasidagi masofani aniqlash mumkin. Rasmda masofa o'lchovlari sifatida eng yaxshi quyi chegara $\left|d_{t_2 a_2} - d_{t_1 a_1}\right|$ olinishi mumkin. O'lchov farqlari uchun (6) tenglama teglararo masofani yaxshiroq hisoblaydi.

B. Ko'p o'lchovli masshtablash (MDS)

MDS-RFID algoritmida klassik MDS o’lchovidan foydalaniladi [20]. MDS o'xshashlik o'lchovlari Evklid fazosi masofalar sifatida ko'rib chiqiladi. MDSning maqsadi chiziqli transformatsiya orqali o'xshashlik o'lchovlariga eng mos keladigan nuqtalarni ko'p o'lchovli fazoda joylashishini topishdir. Bunda riderlar va teglar farq qilmaydi. Misol uchun, m ta nuqtada $\boldsymbol{x}_i$ $(i = 1..m)$ pozitsiyalar bor, $X = [\boldsymbol{x}_1\ \boldsymbol{x}_2 \dots \boldsymbol{x}_m]$ matritsasi $2 \times m$ o'lchamli bo'lsin. Bu yerda lokalizatsiya masalasi 2 o'lchovli deb hisoblanadi. Mayli $D = \left[\hat{d}_{ij}\right]$ juftliklar masofa o'lchovlari matritsasi, $\boldsymbol{x}_i$ va $\boldsymbol{x}_j$ $(i \neq j)$ nuqtalar orasidagi masofa $\hat{d}_{ij}$ va barcha i uchun $\hat{d}_{ii} = 0$. MDS ning maqsadi kuchlanish funksiyasini minimallashtiradigan tekislikda X ning joyini topishdir:

$$\hat{X} = argmin_X Stress(X), \tag{8}$$

bu erda moslikni o'lchaydigan kuchlanish funksiyasi (9) bilan aniqlanadi.

$$Stress(X) = \sqrt{\frac{\sum\left(\hat{d}_{ij} - \|\boldsymbol{x}_i - \boldsymbol{x}_j\|\right)^2}{\sum\|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2}} \tag{9}$$

bu yerda $\boldsymbol{x}_i$ va $\boldsymbol{x}_j$orasidagi Evklid masofasi $\left\|\boldsymbol{x}_i - \boldsymbol{x}_j\right\|$.

Klassik MDSda $\hat{X}$ elementlarini ikki marta markazlashtirilgan kvadrat masofalar matritsasining xos qiymat dekompozitsiyasi (EVD - eigenvalue decomposition) yordamida hisoblash mumkin. D^2 kvadrat masofalar matritsasi $\left[\hat{d}^2_{ij}\right]$ sifatida belgilanadi. Ikki markazli kvadrat masofa matritsa $B_{m\times m}$ elementlari quyidagicha aniqlanadi.

$$b_{ij} = -\frac{1}{2}\left(\hat{d}^2_{ij} - \frac{1}{m}\sum_{k=1}^{m}\hat{d}^2_{kj} - \frac{1}{m}\sum_{k=1}^{m}\hat{d}^2_{ik} + \frac{1}{m^2}\sum_{k=1}^{m}\sum_{l=1}^{m}\hat{d}^2_{kl}\right) = \hat{x}_i^T\hat{x}_j$$

Shuni esda tutish lozimki, B - m musbat xos qiymatga ega bo'lgan musbat aniq matritsa. B matritsasida EVDni bajarish natijalari bo'lgan U va V yordamida $\hat{X}$ ni olish mumkin [21]:

$$B = UVU^T = \hat{X}^T\hat{X}, \quad \hat{X} = UV^{1/2}. \tag{10}$$

In (10), the solution elements Xˆare in m-dimensional space. To reduce it to a two-dimensional space, only the two largest eigenvalues and the corresponding eigenvectors are extracted from V. Now we have the correct size xˆ_i, but they are in relative coordinates. In determining the absolute coordinate, it is necessary to locate the riders in order to find the optimal transformation using the coordinate system registration algorithm [4]. Here only classic MDS, more advanced MDS algorithms can be used when high computing power is available. If classical MDS is adopted, the algorithm is called MDS-RFID(C) (which means C is classical).

C. Improvement

In the last section, the positions given by MDS can be more accurate using maximum likelihood estimation (MLE). As discussed above, the RSS measurement used a logarithmic-normal path loss model. (3) the approximate distance dˆ_ta from the tag to the rider is determined by the formula, the random value of the actual distance d_ta:

ISSN NO: 2770-4491
Date of Publication:11-10-2023

$$\hat{d}_{ta} = 10^{\frac{c-P_{ta}}{10n}} = d_{ta}10^{\frac{z}{10n}} \tag{11}$$

Then, the probability distribution function (PDF) can be defined as d ̂_ta

$$f\left(\hat{d}_{ta}\right) = \frac{10n}{\hat{d}_{ta}\ln 10\sqrt{2\pi\sigma}} e^{-\frac{\left(10n\log\left(\frac{\hat{d}_{ta}}{d_{ta}}\right)\right)^2}{2\sigma^2}}. \tag{12}$$

Turli xil riderlarning masofa o'lchovlari mustaqil deb faraz qilinsa, PDF kuzatuvlari $\left(\hat{d}_{ta_1}, \hat{d}_{ta_2}, \dots, \hat{d}_{ta_{|\mathcal{A}|}}\right)$ quyidagicha hisoblanishi mumkin.

$$f\left(\hat{d}_{ta_1}, \hat{d}_{ta_2}, \dots, \hat{d}_{ta_{|\mathcal{A}|}}\right) = \prod_{i=1}^{|\mathcal{A}|} f\left(\hat{d}_{ta_i}\right) = \alpha e^{\sum_{i=1}^{|\mathcal{A}|} -\frac{\left(10n\log\left(\frac{\hat{d}_{ta_i}}{d_{ta_i}}\right)\right)^2}{2\sigma^2}} \tag{13}$$

where α is a constant, σ is the standard deviation of the noise, and n is the path loss index.

MLE produces a parameter estimate that maximizes the likelihood of an observation. Based on the observation PDF (13), we can develop the MLE for the MDS-RFID algorithm:

$$\hat{x}_t = \text{argmax}_{x_t} f\left(\hat{d}_{ta_1}, \hat{d}_{ta_2}, \dots, \hat{d}_{ta_{|\mathcal{A}|}}\right) = \text{argmin}_{x_t} \sum_{i=1}^{|\mathcal{A}|} \frac{\left(10n\log\left(\frac{\hat{d}_{ta_i}}{d_{ta_i}}\right)\right)^2}{2\sigma^2} \tag{14}$$

by yerda $d_{ta_i} = \left\|\boldsymbol{x}_t - \boldsymbol{x}_{a_i}\right\|$

Problem (14) is a nonlinear optimization problem and does not have a global optimal value. However, this can be solved using some local search methods that provide a good starting point. An important advantage of the MDS-RFID algorithm is that the MDS-estimated uncertain positions provide a better starting solution for pinpointing than other multi-step or heuristic methods. If additional computations are added in refinement, this scheme is called MDS-RFID (C, R). MDS may not always improve the localization results calculated in solving the MLE problem above. If there are multiple riders in an RFID system, MDS using all distances can produce a better topology than refinement using only tag-to-rider distance measurements. As the number of riders increases, adding a refinement stage will prove its advantage.

Algorithm 1 - MDS-RFID algorithm: executed by the RFID system server.
1: All riders in A are registered, RSS measurements are taken from all tags in T.
2: Step 1: Data preprocessing step
3: d ̂_ta is obtained by (4) (∀t ∈T,∀a∈A).
4: Using the triangle method, d ̂_(t_i t_j) (∀t_i t_j ∈T,t_i 〖≠t〗_j) is obtained.
5: Step 2: Multidimensional Scaling (MDS)
6: Running the MDS algorithm using the distance matrix D from step 1 as input.
7: Convert the MDS result to absolute coordinates using the position of the riders.
8: Step 3: Refinement (optional)
9: The result in step 2 is solved with the MLE problem (14) as input.

A full description of the MDS-RFID algorithm is given in Algorithm 1. Lines 2-4 are the data processing step where the RSS measurements in the RFID system describe the distance between pairs. Lines 5-7 give the multidimensional scaling step. Absolute positions of RFID tags can be obtained using classical metric MDS and rider positions. Lines 8-9 correspond to the optional refinement step, which solves the MLE problem using the MDS results in the additional calculation. When there are enough riders in the RFID system, the improvement is effective.

Summary

In pursuit of accuracy, radio frequency identification (RFID) is one of the technologies widely used by researchers to locate objects in various indoor environments. This issue of localization is a complex process, and in the implementation of this process, researchers have conducted research on various advanced algorithms. Above, the most popular algorithms widely used in the localization of RFID tags were studied. Two groups of network-based IPS systems based on information obtained from wireless signals in the indoor environment were studied: distance-based and distance-free methods. Their differences, advantages and

ISSN NO: 2770-4491
Date of Publication:11-10-2023

disadvantages were considered. A description of common methods such as Time-based ToF (Time of Flight) localization, Angle-based AoA (Angle of Arrival) localization, RSS-based localization, Proximity methods, and Fingerprinting methods are given for each method. In addition, the working principles of Passive (Backscatter) RFID systems and several models used in them were analyzed. Popular algorithms such as the nearest neighbor method, artificial neural network, and support vector machine used in the initial analysis of the localization region, which is considered an important step in localization, were analyzed. At the same time, each stage of the Multi-Dimensional Scaling (MDS-RFID) algorithm, which is the most effective in localization today, and the models used in them were discussed separately.

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