ARTICLE IN PRESS

Journal of King Saud University – Computer and Information Sciences xxx (xxxx) xxx

Contents lists available at ScienceDirect

Journal of King Saud University – Computer and Information Sciences

journal homepage: www.sciencedirect.com

Localization strategies for autonomous mobile robots: A review

Prabin Kumar Panigrahi *, Sukant Kishoro Bisoy

Department of Computer Science and Engineering, C. V. Raman Global University, Bidya Nagar, Mahura, Janla, Bhubaneswar, Odisha 752054, India

A R T I C L E I N F O

Article history:
Received 27 October 2020
Revised 18 January 2021
Accepted 27 February 2021
Available online xxxx

Keywords:
Mobile robot localization
Probabilistic approach
RFID
SLAM
Evolutionary approach

A B S T R A C T

Localization forms the heart of various autonomous mobile robots. For efficient navigation, these robots need to adopt effective localization strategy. This paper, presents a comprehensive review on localization system, problems, principle and approaches for mobile robots. First, we classify the localization problems in to three categories based on the information of initial position of the robot. Next, we discuss on robot position update principles. Then, we discuss key techniques to localize the mobile robot such as: probabilistic approach, autonomous map building and radio frequency identification (RFID) based scheme. In the probabilistic localization section, we discuss the Markov localization and Kalman filter along with its extended versions. Autonomous map building focuses on the widely used simultaneous localization and mapping (SLAM) approach. This section also discusses on applying SLAM to localize brain-controlled mobile robots. Next, we discuss on applying evolutionary approaches to estimate optimal position. The RFID scheme addresses on effective utilization of RFID tags to track objects and position the robot. We then analyze on position and orientation errors occurred by different localization strategies. We conclude this paper by highlighting future research possibilities.

Contents

* Corresponding author.
E-mail addresses: prabinprakash1@gmail.com (P.K. Panigrahi), sukantabisoyi@yahoo.com (S.K. Bisoy).

Peer review under responsibility of King Saud University.

ELSEVIER Production and hosting by Elsevier

https://doi.org/10.1016/j.jksuci.2021.02.015

1. Introduction

Mobile robots have remarkable achievement in industrial manufacturing, medical science, social science, agriculture, education, games, space research etc. Navigation is a challenging problem for autonomous mobile robots. To perform successful navigation, the robot passes through different phases such as: perception, localization, cognition and motion control. In the perception phase, the robot extracts meaningful data by interpreting its sensors. In the localization phase, the robot estimates its current location in employed environment using information from external sensors. In the cognition phase, the robot plans the necessary steps to reach the target. The motion control phase lets the robot achieve its desired trajectory by modifying its motor outputs. In the past decade, localization has received the greatest research attention (Siegwart et al., 2011). Rest of this paper focuses on the localization problem and different strategies developed for positioning autonomous robots.

Based on the information of initial position, we classify the localization problem in to position tracking, global positioning/localization, and kidnapped robot problem. In position tracking, the robot's initial position is known and the objective is to track the robot at each instance of time during its navigation in the environment. During navigation, the localization algorithm utilizes the robot's previous position to update its current location. This is possible by continually monitoring the route of the robot. Position tracking utilizes odometry and sensor data. However, in case of large uncertainty, the robot might not be localized. Hence, in position tracking, the position uncertainty of the robot is required to be small. Moreover, in position tracking, the robot's initial *belief* (best guess about initial state) is a normal distribution.

Relocation deals in mobile robot tracking without any information on its initial pose. This gives rise to another class of localization problems: global localization. In this category, the robot does not have any knowledge about its initial position. This signifies that the robot is able to locate itself globally within the environment (Negenborn, 2003). In some situations, the robot is tracked at an arbitrary place sometimes during pose tracking or abducted (kidnapped) to an unidentified place. This issue arises in kidnapped robot problem where, the robot knows that it is being kidnapped. Hence, Kidnap recovery is necessary for any autonomous robots. In most of the situations, the current sensor data is utilized in estimating its pose. Basically, the best match between known data and sensor data solves the issue of relocation. An autonomous robot should be able to handle pose monitoring and relocation simultaneously. It should be able to recognize that; it is being kidnapped and it should recover its pose by applying relocation method.

The above three localization problem deserve special attention in the research in mobile robot localization. As per our study the position tracking problem dominates other two categories (Fig. 1). Different authors developed various approaches for addressing these problems. This includes probabilistic localization strategies, automatic map-based localization, RFID based approaches and evolutionary techniques applied to these for optimizing the robot position estimation.

However, the environment's dynamics influences each of these problems. The robot's environment can be either static or dynamic. In static environment, localization is quite simple as the robot is the only moving object. In dynamic environment, localization is significantly more difficult, because the robot gets confused about its location due to presence of other moving objects. Autonomous movement control is a challenging factor for mobile robots employed in unknown environments. In unfamiliar zones, the robot learns the environment's map during navigation. This approach is known as simultaneous localization and mapping (SLAM).

In this review paper, we have analyzed over 100 papers, and present a comprehensive review and analysis on different localization techniques developed for positioning autonomous mobile robots. a classification of mobile robot localization problems. In Section 2, we address basic localization principle and its phases. Section 3, presents the probabilistic localization techniques, automated map building and radio frequency identification (RFID) approach to localize mobile robots. Analysis on position and orientation errors occurred during localization is discussed in Section 4. Finally, Section 5 concludes this paper by highlighting current issues and future research direction.

2. Localization principle

A mobile robot keeps track of its motion using odometry while navigating in a known environment. However, odometry uncertainty confuses the robot about its current position. Therefore, the robot should localize itself concerning the map of its environment. This also results in keeping the position uncertainty from growing unbounded. For localization, the robot utilizes its exteroceptive sensors such as laser sensor, vision and ultrasonic sensor to make observation about its environment. The sensors information can be combined with robot's odometry to localize the robot. Basically, even with global positioning sensor (GPS), the robot's

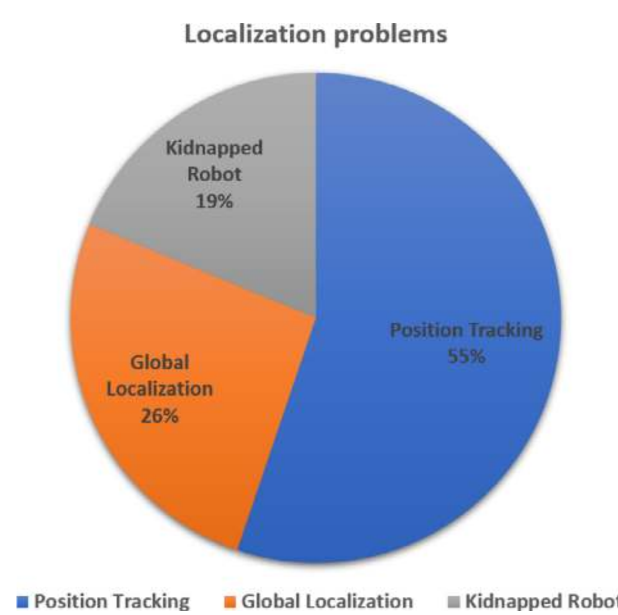

Fig. 1. The percentage of each category of mobile robot localization problems.

accurate position can't be measured directly. The robot can only extract its sensors data to gain knowledge regarding the best estimate about its location. The robot's belief is denoted by S_{Best}. The general process of robot's position update has two steps:

- prediction/action update
- perception/measurement/correction update.

The beliefs about configuration of the robot are usually represented as probability density functions (PDF) (Siegwart et al., 2011).

During *prediction update* the robot utilizes its proprioceptive sensors (e.g. Wheel/motor sensor, acceleration sensor) to estimate its position. However, due to odometry error, the uncertainty about the robot configuration increases (Fig. 2(a)). The initial position x_0 is known, and hence the PDF is a *Dirac delta* function. When the robot navigates, due to odometric error, the uncertainty grows and it accumulates over time.

The robot corrects the estimated position (outcome of prediction phase) using its onboard exteroceptive sensors in the *perception update* phase. The robot uses rangefinder to calculate its present distance d from the right wall and computes the position x'_2. This position conflicts with the present position x_2 estimated in the prediction phase. The measurement update corrects the new location to x''_2. Consequently, the uncertainty shrinks (solid line) (Fig. 2(b)).

Below we discuss the mathematical analysis to update the robot's estimated position. We can define the position as:

$$p = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} \tag{1}$$

The current position of a differential-drive can be estimated from its initial position information by adding the incremental travel distances ($\Delta x;\Delta y;\Delta\theta$), where,

$$\Delta x = \Delta s \cos\left(\theta + \frac{\Delta\theta}{2}\right) \tag{2}$$

$$\Delta y = \Delta s \sin\left(\theta + \frac{\Delta\theta}{2}\right) \tag{3}$$

$$\Delta\theta = \frac{\Delta s_r - \Delta s_l}{b} \tag{4}$$

$$\Delta s = \frac{\Delta s_r + \Delta s_l}{2} \tag{5}$$

It may be noted that the experimented system is discrete and the sampling interval Δt is fixed.

Here, ($\Delta x;\Delta y;\Delta\theta$) denotes the robot's path in the last sampling interval;

Δs_r is the distances travelled for the right wheel.
Δs_t is the distances travelled for the left wheel.

The updated position p' can be calculated as

$$p' = \begin{bmatrix} x' \\ y' \\ \theta' \end{bmatrix} = p + \begin{bmatrix} \Delta x \\ \Delta y \\ \Delta\theta \end{bmatrix} = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} + \begin{bmatrix} \Delta x \\ \Delta y \\ \Delta\theta \end{bmatrix} = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} + \begin{bmatrix} \Delta s \cos\left(\theta + \frac{\Delta\theta}{2}\right) \\ \Delta s \sin\left(\theta + \frac{\Delta\theta}{2}\right) \\ \Delta\theta \end{bmatrix}$$

Replacing $\Delta\theta$ and Δs by Eqs. (4) and (5) respectively, we have,

$$p' = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} + \begin{bmatrix} \frac{\Delta s_r + \Delta s_l}{2} \cos\left(\theta + \frac{\Delta s_r - \Delta s_l}{2b}\right) \\ \frac{\Delta s_r + \Delta s_l}{2} \sin\left(\theta + \frac{\Delta s_r - \Delta s_l}{2b}\right) \\ \frac{\Delta s_r - \Delta s_l}{b} \end{bmatrix} \tag{6}$$

where, b is the distance between the wheels of differential-drive robot (Siegwart et al., 2011).

The position error grows over time due to integration errors of the uncertainties of p and the motion errors occurred during incremental motion ($\Delta s_r;\Delta s_l$).

3. Localization approaches

In this section we analyze mobile robot localization approaches from two different perspectives: Probabilistic approaches and autonomous map building. In the first category we discuss Markov localization, Kalman filter (KF) and other approaches. Next, we discuss SLAM approaches for automatic map construction during mobile robot localization. Further we analyzed on applying RFID technique to mobile robot localization. Finally, we ended this section with discussing different evolutionary approaches applied to above strategies for providing optimized position estimation.

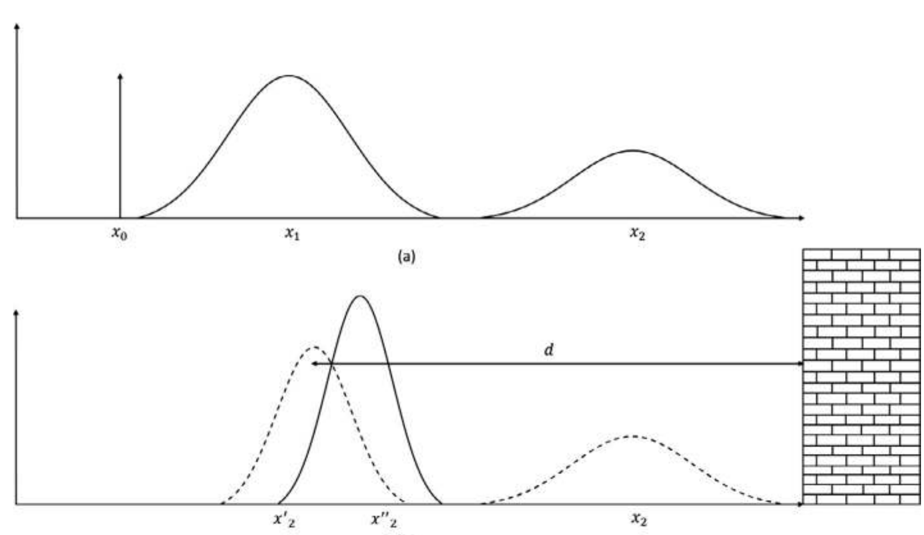

Fig 2. Prediction and perception phase (a) Prediction phase (b) Perception phase (Siegwart et al., 2011).

3.1. Probabilistic approaches

Probabilistic map-based localization approaches identify the probabilities of robot being in specific positions. The measurement errors affect the sensor data. Therefore, the probability of a robot in a specific configuration can only be computed.

- Markov localization
- Kalman filter localization

In both approaches, the *theorem of total probability* is applied in the prediction update phase. However, the *Bayes rule* is used for perception update (Siegwart et al., 2011).

3.1.1. Markov localization

The Markov localization addresses the three localization problems (mentioned in Section 2) in efficient manner. The robot can locate itself starting from an *unknown* position. Multiple possible positions can be tracked by the robot. Therefore, the Markov localization can recover from ambiguous situations. However, the state space needs to represented in a discrete way for updating the probability of possible positions. This discrete representation may be a topological graph or a geometric grid. The memory requirement for map size is limited.

In the prediction update phase, the robot's current location is estimated depending on the available information on previous locations and odometry input. The robot's current state $\overline{S_{Best}}(x_t)$ can be computed from the previous estimated position $\overline{S_{Best}}(x_{t-1})$ and proprioceptive data (control input) u_t:

$$\overline{S_{Best}}(x_t) = \sum_{x_{t-1}} p(x_t|u_t, x_{t-1}) S_{Best}(x_{t-1}) \quad \text{(in discrete representation of map)}. \tag{7}$$

$$\overline{S_{Best}}(x_t) = \int p(x_t|u_t, x_{t-1}) S_{Best}(x_{t-1}) dx_{t-1} \quad \text{(in continuous representation of map)}. \tag{8}$$

Where, In the perception or measurement update phase, the robot corrects its earlier position by combining it with the exteroceptive sensors input. The Bayes rule is applied to calculate the robots new state $S_{Best}(x_t)$ as a function of its measurement data z_t and previous state $\overline{S_{Best}}(x_t)$:

$$S_{Best}(x_t) = \eta p(z_t|x_t, M) \overline{S_{Best}}(x_t) \tag{9}$$

where, x_t denotes the robot's position and $p(z_t|x_t, M)$ is the probabilistic measurement model: the change of coordinates from the world frame to the sensor reference frame (a part of the robot). It signifies the probability of observing z_t given the knowledge of robot poses x_t and map M. The probabilistic measurement model is computed from a noise-free measurement function h which depends on M and x_t.

As demonstrated in Fig. 2, the robot utilizes a rangefinder to measure its distance d (the observation) from the right wall. Therefore $z_t = d$. Here, M is signified by a single feature m (the wall). Assuming the robot navigates in a one-dimensional environment and the wall is at coordinate 20 i.e. $m = 20$, the measurement function h can be calculated as: $h(x_t, M) = 20 - x_t$.

To derive the probabilistic measurement model a noise term is added to the measurement function such that the probabilistic distribution $p(z_t|x_t, M)$ peaks at $h(x_t, M)$ which is noise-free. Assuming Gaussian noise we have,

$$p(z_t|x_t, M) = N(h(x_t, M), R_t) \tag{10}$$

where N denotes a multivariate normal distribution having mean $h(x_t, M)$ and noise covariant matrix R_t.

Fig. 3 demonstrates the flowchart for Markov Localization.

The Markov localization model can represent any arbitrary PDF over the robot position.

3.1.2. Kalman filter-based localization

The Kalman filter-based localization solves the position tracking problem in efficient and precise manner. It is an optimal sensor-fusion approach which tracks the robot from an *initially* known location. Usually, this localization can be used in continuous world representation. However, in certain situations, the robot's uncertainty is too large (may be when the robot collides an object) and therefore not really unimodal. In this case the localization approach can't capture the possible robot positions and becomes lost irrevocably.

Kalman filter is a special case of Markov localization. It does not use arbitrary density function. Instead, it uses Gaussians to represent the robot's assumption $S_{Best}(x_t)$, the motion model, and the measurement model. Fig. 4. represents the schematic diagram of applying Kalman filter to localize mobile robot.

The first phase i.e. the *prediction update* directly applies a motion model having Gaussian error to the robot's measured encoder travel.

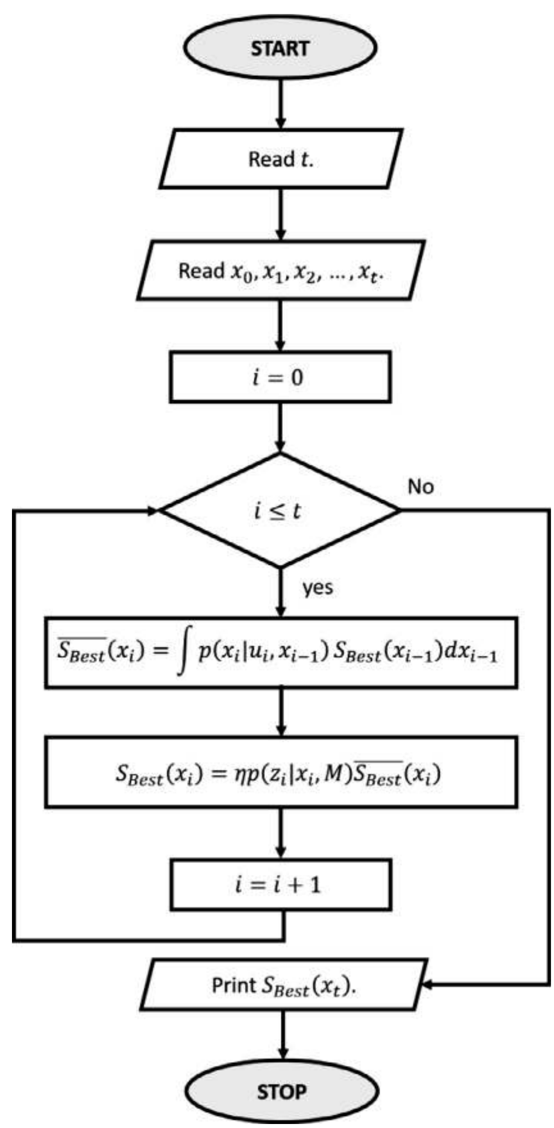

Fig. 3. Flowchart for Markov Localization.

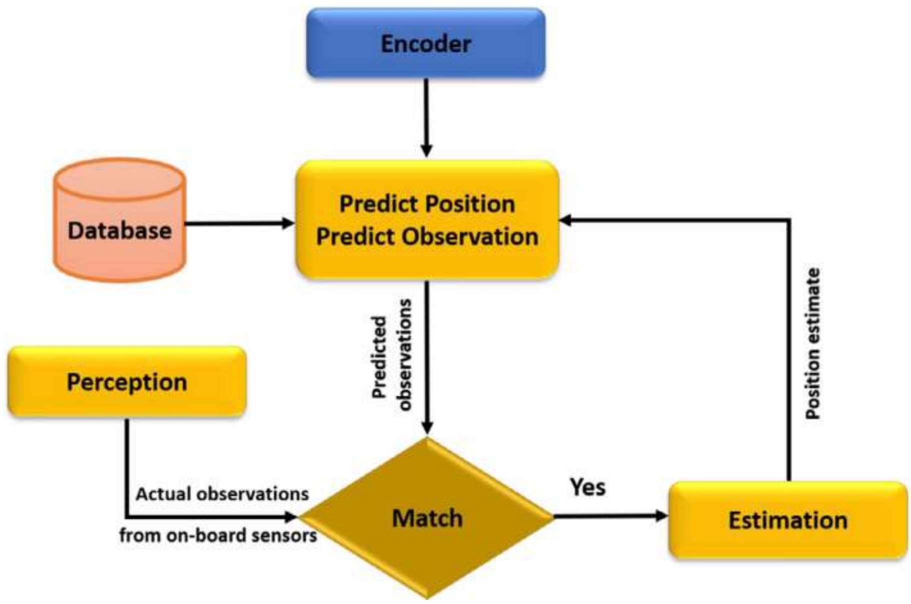

Fig. 4. Schematic diagram of Kalman filter-based mobile robot localization.

The *perception update* phase follows the following four steps:

Step 1. Observation step:
From the sensor data, the robot extracts different features such as specific sensor value, doors, lines etc.
Step 2. Measurement/Perception prediction:
The robot produces a *measurement prediction* consisting of features that it expects to observe from its assumed positions that is from the outcomes of prediction step.

Step 3. Matching:
In this phase the robot computes the best match between features extracted from observation and features (expected) selected during the measurement prediction.
Step 4. Estimation:
To update the robot belief state in the estimation step, the Kalman filter fuses the matching information.
For Gaussian distribution the normal PDF can be defined as

$$p(x) = \frac{1}{\sigma\sqrt{2\pi}} exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{11}$$

where,

x: scalar random variable.
μ: the mean of the x.
σ^2: the variance of x.

However, if x is a k-dimensional vector, a multivariate normal distribution (Eq. (12)) is used.

$$p(x) = \frac{1}{\sqrt[k]{2\pi}|\sqrt{\sum}|} exp\left(-\frac{(x-\mu)^T}{\sum^{-1}(x-\mu)}\right) \tag{12}$$

where μ is the mean vector and Σ is a symmetric and positive semidefinite matrix called covariance matrix.

The Kalman filter uses the odometry model for estimating the robot position. Suppose that for a differential-drive robot, the best position estimation at time $t-1$ is

$$x_{t-1} = \begin{bmatrix} x_{t-1} \\ y_{t-1} \\ \theta_{t-1} \end{bmatrix} \tag{13}$$

Say after sometime the robot drives to new position $\hat{x}_t$. Applying equation-6, this new position $\hat{x}_t$ at time t can be predicted from previous estimated position x_{t-1} as

$$\hat{x}_t = f(x_{t-1}, u_t) = \begin{bmatrix} x_{t-1} \\ y_{t-1} \\ \theta_{t-1} \end{bmatrix} + \begin{bmatrix} \frac{\Delta s_r + \Delta s_l}{2} \cos\left(\theta_{t-1} + \frac{\Delta s_r - \Delta s_l}{2b}\right) \\ \frac{\Delta s_r + \Delta s_l}{2} \sin\left(\theta_{t-1} + \frac{\Delta s_r - \Delta s_l}{2b}\right) \\ \frac{\Delta s_r - \Delta s_l}{b} \end{bmatrix} \tag{14}$$

where,

Δs_l: the left wheel displacement.
Δs_r the right wheel displacement.
The control input is $u_t = \begin{bmatrix} \Delta s_l \\ \Delta s_r \end{bmatrix}$.

In Kalman filter localization, the Gaussian is defined by mean μ_t and covariance $_t$. During prediction and measurement phase, these parameters are updated. Therefore, compared to Markov Localization, Kalman filter is very efficient. However, in Kalman filter approach the robot initial position should be known with a certain approximation. Therefore, if the robot gets lost, it can't recover its position. This is in contrast with Markov localization. Hence, the position tracking problem is effectively solved using Kalman filter. However, it does not solve the global localization and the kidnapped robot problem.

Within the theory of Kalman filter, the system is supposed to be *linear* and with *Gaussian* noise. However, many robotic systems require the system to be nonlinear. This gives rise another localization approach commonly known as the extended Kalman filter (EKF). EKF is the extension of Kalman filter to nonlinear systems. In EKF, first the system is linearized and then Kalman filter is applied. The EKF represents a Gaussian probability distribution, and allows simple parameterization as a matrix for covariance and mean. Leonard and Durrant-Whyte (1992) used EKF based approach in a sonar sensor model for localizing a mobile robot. Schiele and Crowley (1994) applied EKF in occupancy grid based on a Hough transform framework (HTF). Gutmann and Schlegel (1996) proposed combined scan matcher (CSM) algorithm which combines extended Cox and iterative dual correspondence (IDC) algorithms for mobile robot self-localization. Chen et al. (2012) adopted a filtering approach based on EKF that utilizes feature map for positioning mobile robots. Comparison of KF and EKF is addressed in Suliman et al. (2010). The simulated analysis shows that, in comparison to KF, EKF performs significantly better in mobile robot position estimation.

There are other probabilistic localization techniques that have been used in mobile robot research platforms such as unscented Kalman filter (UKF), grid-based localization and Monte-Carlo localization (MCL). Like EKF, the UKF also assumes Gaussian distributions. However, the UKF applies *unscented transform* to linearize the motion and measurements models. In contrast, grid-based localization and MCL are not bounded by unimodal distributions. In grid localization, the robot belief is represented by the histogram filter. The MCL uses particle filters to represent the robot belief. It uses a subset of the whole set of possible positions to construct the approximate belief state for the robot. This results in tracking and updating a small number of possible locations instead of all possible locations which in turn reduces the complexity. Different authors applied MCL for positioning mobile robots. Dellaert et al. (1999a) addressed a probabilistic method with sampling-based representation for localization. Klaess et al. (2012) utilized MCL with probabilistic observation models on 3D grid maps. In static environment average tracking error is characterized in terms of distance and angular error. In dynamic environment multiple persons randomly walk and the objective is to evaluate frequency and accuracy of suggested localization approach while estimating final position of the trajectory. Uniform distributions of 5000 particles are used for global localization.

Various authors adopted vision-based tracking system for mobile robots. Krumm et al. (2000) developed a person-tracking system utilizing colour stereo cameras (two sets). In an indoor environment, such as living room, the proposed system tracks multiple people. Yan et al. (2011) presented a particle filter (PF) based person tracking system. The PF receives input from vision streams such as: Sigma-Pi-like network. To locate mobile robots, Dellaert et al. (1999b) developed a Bayesian filtering approach (CONDENSION algorithm) which makes use of density representation based on sampling.

Beacon based and radio frequency schemes are adopted by different authors for developing effective object positioning system in intelligent environments (Want et al., 1992; Shirehjini et al., 2012; Bahl et al., 2000; Ekkahau Inc., 2019; Ubisense Products, 2019). Want et al. (1992) proposed an active badge system to be applied in office environment. In this system, an active badge is wearied by each office individuals. This badge or tag emits a distinctive code for around $(1/10)^{th}$ of a second in 15 s duration. This signal is received by a network sensor placed in a centralized location. The tag is responsible to determine the position of an individual. The suggested scheme utilizes a beacon network which communicates with IR signals modulated by pulse width to locate users in intelligent office environments. However, one main issue is that: an additional device is required to be carried by each individual for allowing the system to locate him or her (Shirehjini et al., 2012). Shirehjini et al. (2012) proposed an efficient methodology which results in low average error to place and orient indoor object. Bahl et al. (2000) addressed a radio frequency (RF)-based beacon scheme which uses the RADAR system to track and position indoor users. As reported in Ekkahau Inc. (2019); Beacon based systems embedded with WiFi technology produces effective result in robot localization. Other localization technique includes the ultra wide band (UWB) method for object positioning (Ubisense Products, 2019).

Yamada et al. (1996) used sound-based localization to locate objects through sound. However, this approach is not applicable for non-sound producing objects. Ashokaraj et al. (2009) developed a multi-sensory system (MSS) based localization which is a deterministic technique for mobile robots using interval analysis. These robots utilize ultrasonic sensors as sensor technology. Georgiev and Allen (2004) used GPS based scheme which is applicable for locating robots employed in urban areas. Burgard et al. (1996) proposed a probabilistic grid approach for mobile robot position estimation. The suggested method relies on Bayesian scheme and is applicable in positioning robots even if with the presence of noisy ultrasonic sensors and occupancy grid maps which are the approximate environmental models. In indoor environment especially office, Simmons and Koenig (1995) used partially observable Markov model (POMM) to position the robot. The state space is organized in this strategy in accordance with the topological environment structure. However, this model requires the grid-size to be predetermined. Neto et al. (2009) proposed complementary filtering (CF) technique for mobile robot localization and orientation estimation, by fusing data gathered from GPS, digital compass and inertial measurement unit (IMU). This results in low implementation cost and high-quality result for robot navigation in outdoor environment. Rampinelli et al. (2014) presented a TCP/IP based client–server system in intelligent space which localizes and controls different types of robots including robotic wheelchairs. The proposed system constitutes 11 cameras for synchronous image capturing. The server makes connection with each of these cameras and robot. The server collects various sensors data, processes them and sends the outcome to client. For localization, a calibration technique is suggested which utilizes the multi-camera network. First, the robot passes a model of calibration throughout the camera field of perspective. Next, the proposed calibration method uses robot odometry and captured images. This offers a solution to simultaneously locate the robot and calibrate multiple cameras. Vasiljević et al. (2016) proposed a hybrid localization approach which combines adaptive MCL (AMCL), iterative closest point (ICP) and discrete Fourier transform (DFT). This hybrid algorithm provides sub-centimeter positioning accuracy in real time environments such as industries. The AMCL algorithm fuses laser range measurements with odometry data to provide a known covariance for robot pose estimation. Next the ICP algorithm uses that result as an initial estimate. Finally, the output of ICP algorithm is fed to a DFT technique, that returns the final outcome. Zi et al. (2015) created an improved algorithm for localization based on multilateration approach. Choi et al. (2012a) proposed an effective localization technique to simultaneously solve pose monitoring and kidnap recovery. Table 1 presents a comparison among basic localization approaches and the advantages and drawbacks of different approaches are presented on Table 2.

3.1.3. Evolutionary approaches

Different authors applied evolutionary approaches such as particle swarm optimization (PSO) (Havangi, 2019; Vahdat et al., 2007; Huo et al., 2013; Havangi et al., 2010; Pinto et al., 2015; Dastjerdi et al., 2016; Mali, 2015), genetic algorithm (GA) (Armingol et al., 1999; Wang et al., 2015; Rajurkar et al., 2016), FLC and differential evolution (DE) to basic localization techniques like EKF, MCL, PF etc. for determining the robot location. Havangi (2019) proposed a PSO based localization technique which overcomes several issues found in PF based schemes. Localization using PF has major issues such as degeneracy and impoverishment problem which reduces its performance. The proposed method establishes a recursive framework for tracing out the robot position. This is achieved by converting the robot localization to dynamic optimization. The developed scheme neither requires resampling phase as in PF based methods nor distribution of noise. To estimate the robot position, a stochastic search technique is implemented in the state-space. The proposed PSO based approach is proved to be more efficient in comparison with standard PF and EKF based localization techniques. The lower root mean squared error (RMSE) of

Table 1
Analysis of existing localization systems.

Reference	Approach	Application Environment	Simulation and Experiment	Sensor technology
Leonard and Durrant-Whyte (1992)	EKF in model-based localization system.	Indoor	Experiment: SKIDS vehicle and Oxford Robuter. Configuration: Two microprocessors: 68,000 (to control sonar data bus) and 68,020 vehicle controllers.	SKIDS vehicle: Six static sonar sensors. Oxford Robuter: Eight static sonar sensors.
Schiele and Crowley (1994)	KF-EKF in occupancy grid.	Indoor Hall-way	Simulation: Graphical.	NA
Gutmann and Schlegel (1996)	CSM	Indoor	Simulation: Graphical.	NA
Chen et al. (2012)	EKF in feature map.	Virtual Environment: The robot navigates in a circular trajectory.	Simulation: Graphical (with mathematical proof).	NA
Suliman et al. (2010)	KF vs. EKF	Generic	Simulation: MATLAB. Experiment: Ackermann steering based autonomous mobile robot.	NA
Dellaert et al. (1999b)	Probabilistic MCL.	Indoor	Experiment: RHINO (RWIB21 robot) and MINERVA (RWIB18 robot).	Sonar sensor
Klaess et al. (2012)	MCL in 3D grid map.	Indoor	Simulation: Graphical.	NA
Krumm et al. (2000)	Vision-based person tracking system.	Indoor	Simulation: Person tracking system (in living room).	Vision sensor (color stereo cameras).
Yan et al. (2011)	Vision-based object tracking system.	Indoor	Experiment: Tested in a living room and with CLEAR 07 dataset representing distracter person.	Vision sensor (color camera)
Dellaert et al. (1999b)	Vision-based MCL.	Outdoor	Experiment: MINERVA (RWIB18 robot).	Upward pointing camera
Want et al. (1992)	Beacon-based approach.	Indoor	Experiment: Used by PBX clients. Installed at ORL. Tested at Xerox EuroPARC, Olivetti STL, Xerox PARC, MIT Media Laboratory.	Badge sensor.
Bahl et al. (2000)	RF based beacon system.	Indoor	Experiment: Tested in RADAR testbed.	RF reader.
Ashokaraj et al. (2009)	MSS based localization.	Generic	Experiment: Virtual robot (A robot model with rear wheels (powered) and front wheels (steerable) to navigate in a 2D map).	Ultrasonic sensor.
Georgiev and Allen (2004)	GPS	Outdoor (urban areas)	Experiment: ATRV-2 robot manufactured by iRobot.	Sonar sensor and camera.
Burgard et al. (1996)	Bayesian approach.	Indoor	Experiment: RHINO robot.	Ultrasonic sensors.
Simmons and Koenig (1995)	POMM model.	Indoor	Experiment: Xavier (RWI B24) robot.	Laser range sensor, bump sensors, sonar sensor and a color camera.
Neto et al. (2009)	CF	Outdoor	Experiment: Pioneer P3-AT robot.	IMU, GPS, digital compass and odometry sensor.
Rampinelli et al. (2014)	intelligent space system (ISS)	Indoor	Experiment: Pioneer 3 AT (P3-AT) robot.	Cameras.
Vasiljević et al. (2016)	AMCL + ICP + DFT	Indoor industrial	Experiment: LGV1000 vehicle prototype.	Laser sensor.
Choi et al. (2012a)	Topological localization.	Indoor home	Experiment: PIONEER3-DX robot.	12 MA40B8 sonar sensors.

position and heading (<0.2) proves that the efficiency of the suggested approach is better than that of other algorithms in any environment. Vahdat et al. (2007) presented a hybrid localization approach which combines DE with PSO. The proposed methods are compared with standard MCL and proved to give better result because of faster convergence and robustness. In Huo et al. (2013) Junfei et al. proposed a DEPSO algorithm (DE + PSO). The first phase utilizes the selection and mutation operations of standard DE approach and then swarms best position is updated by PSO. The next phase updates velocity and position of particles using PSO followed by crossover and selection by DE. The two challenging criteria such as global optimization (of DE) and fast convergence (of PSO) makes DEPSO robust and powerful. This research compares the localization accuracy of PF and DEPSO in the case of a known initial position. The result of applying PF and DEPSO with 2000 particles proves DEPSO to be more stable and accurate in positioning.

Further Havangi et al. (2010) proposed an effective multi swarm PF for robot positioning. The major focus of this approach is increasing the performance of PF by PSO. This overcomes the localization impoverishment occurred in PF based scheme. Pinto et al. (2015) combined PSO with standard EKF for estimating the robot's current position. The EKF combines map-matching, position and orientation estimation and dead-reckoning approach. This result in reliable position tracking. However, in case of high error in map-matching, the proposed localization system applies PSO to relocate the robot. This is because, unreliable map-matching makes the robot go missing. The large map-matching error in the present estimate outcomes in low confidence. In this situation, PSO globally localizes the robot. Therefore, over the global map, a set of particles are published to search the room with high confidence to discover an outcome. In this paper, the estimation of pose is obtained by using the RPROP (Resilient Propagation) for error function minimization. The proposed system analyses the pose error in virtual and realistic scenario.

Dastjerdi et al. (2016) developed a self-localization approach for localizing soccer humanoid robots using image processing. It

Table 2
Comparisons among different probabilistic localization approaches.

Reference	Approach	Advantages	Drawbacks
Leonard and Durrant-Whyte (1992)	EKF in model-based localization system.	The robot maintains continuous map contact, almost effortlessly gliding through its environment, "grabbing hold" of cylinders, planes, and corners in the environment.	It can't utilize autonomous model for model-based tracking.
Schiele and Crowley (1994)	KF-EKF in occupancy grid.	The occupancy grid can also support obstacle avoidance of very small obstacles.	When following a wall, the occupancy grid technique without EKF can falsely constrain the position uncertainty of the robot, resulting in an inability to match when other features are encountered.
Gutmann and Schlegel (1996)	CSM	Results in a very low position error while performing navigation.	–
Chen et al. (2012)	EKF in feature map.	The distance error between the estimated position calculated from EKF and the ground truth remains almost the same level.	The proposed algorithm is implemented in *a priori* map which may not be always available.
Suliman et al. (2010)	KF vs. EKF	The EKF performs significantly better than the KF.	–
Dellaert et al. (1999b)	Probabilistic MCL.	The proposed method efficiently localizes a mobile robot with no prior information about its initial location.	Due to the repeated selection of hight weight samples the proposed system results in a loss of diversity.
Klaess et al. (2012)	MCL in 3D grid map.	To localize globally especially in crowded environment, the proposed approach is quite accurate and robust.	The proposed approach is not tested in 6-DOF robot in dynamic environment.
Krumm et al. (2000)	Vision-based person tracking system.	This approach is proved to be challenging in tracking multiple people in dynamically changing environment.	–
Yan et al. (2011)	Vision-based object tracking system.	The feature pattern used for one cue, provides robust identification of a person and is quite effective in object detection and tracking in complex conditions.	The proposed system depends only on the four cues, and not on other features. Non-visual sensors such as microphones can be used to gather more data to improve the tracking accuracy.
Dellaert et al. (1999b)	Vision-based MCL.	In dynamic unmodified environment, the proposed system is able to both globally localize and locally track the robot.	The proposed approach is not tested on less sensory inputs (for example, by omitting the wheel encoders that provide odometry measurements).
Want et al. (1992)	Beacon-based approach.	It is a very useful office system for tracking office employees.	RF signal propagation is influenced by phenomenon such as absorption, diffraction, diffusion, and reflection.
Ashokaraj et al. (2009)	MSS based localization.	The proposed approach does not require any separate data matching algorithm to recognize the environment of the robot. In addition to that, it does not require any separate initialization method.	–
Georgiev and Allen (2004)	GPS	The proposed system is quite effective for mobile robots employed in urban areas.	• The high degree of repetitiveness may lead to a confusion in the matching process. • It uses only one of the visible building facades even if more may be present.
Burgard et al. (1996)	Bayesian approach.	The proposed system does not require any priory information on the initial position of the robot. It is proved to be robust in ambiguous situations.	–
Simmons and Koenig (1995)	POMM model.	The proposed system effectively deals with uncertainty in the robot's initial position, actuator uncertainty, sensor noise, and uncertainty in the interpretation of the sensor data.	• The action selection heuristics enter a limit cycle and continually turn the robot. • The robot's position estimation becomes inaccurate when the obstacle avoidance algorithm moves the robot a significant distance orthogonally to its commanded heading.
Neto et al. (2009)	CF	The significant reduction of the computational complexity of the overall system, enables increasing the sampling frequency of the signals with a consequent improvement in the accuracy of the estimates.	• The behaviour of the system needs to be analyzed based on experiments with large vehicles. • It is necessary to perform better analysis and treatment of the GPS altitude data.
Rampinelli et al. (2014)	Intelligent space system (ISS)	The proposed system is quite efficient in localizing robotic wheelchairs.	• The proposed approach needs to be applied in intelligent space to control mobile robots with limited onboard sensors. • The calibration algorithm needs to be tested with non-overlapping field of view with all 11 cameras. • Further there should be adjustments for the on-line multi-camera calibration procedure.
Vasiljević et al. (2016)	AMCL + ICP + DFT	In industries, the proposed methodology is quite challenging to localize AGVs with high-precision.	The performance of this system needs to be tested on vehicles in motion.
Choi et al. (2012a)	Topological localization.	• The grid map matching method and motion model tracks the robot's pose quite effectively. • Kidnap detection and recovery methodology is very challenging. • To return to the pose tracking stage, the hypothesis selection is very reasonable in kidnap recovery process.	–

converts the obtained image into an image taken from the top view by an inverse perspective map. Then it utilizes PSO to define the robot's location relative to origin. The proposed method recognizes position based on captured images. The Robot could do the self-localization in 94% success and 6% failure. In this state, more than 300 mm distance error and 15° angle are considered for inability in self-localization. The method achieves high accuracy as it utilizes ground lines points for self-localization. With some set of points this method can recognize its own position. This causes it to be very noise resistant. Mali (2015) combined PSO and ant colony optimization (ACO) to estimate the robot location. PSO is used for weight adjustment and ACO utilizes the neural network topology.

Armingol et al. (1999) developed an iterative EKF procedure, which uses an a priori map of beacon positions and observed geometric beacons to correct the pose of the vehicle. The GA is applied in tracing out the vehicle's optimal position. The proposed methodology makes extensive use of ultra-sonic sensor. It applied relocation approach based on matching between the environment map and sensorial information to decrease the estimated location error and uncertainty. Robot's current position is estimated with a population size of 250. The pose error analysis with 5 and 10 generations are presented. The major issues in standard EKF based robot localization is determination of error covariance matrices Q and R in time variant. Wang et al. (2015) proposed GA-fuzzy logic controller (FLC) to adjust the covariance matrices. GA makes the system more powerful because it tunes the fuzzy membership functions (MF) which results in improving FLC's accuracy. Finally, the comparison among EKF, fuzzy logic (FL)-based EKF and EKF based on GA-FL proves that GA-FL based EKF technique provides accurate result in comparison other two approaches. Further Rajurkar et al. (2016) extended this idea and developed a fuzzy controller-based computer vision (CV) approach for path tracking and robot position and orientation estimation. The CV approach detects and locates the neighborhood target. Here the control system based on fuzzy inference tracks the estimated path removing heavy computations and iterative updates. Moreover, GA is involved to optimize input–output membership functions.

Neto et al. (2019) proposed leader-based Bat algorithm (LBBA) method to search robot's best location by employing a smaller number of micro bats as leaders in pursuit of the best place to impact the colony. Using this approach, the localization ambiguity is dealt satisfactorily. Compared with the AMCL algorithm which uses a variable number of particles, the proposed technique showed average error below the expected tolerance of 21%. The average error presented here is based on experiment in real robot. This approach deals with ambiguities in robot localization. The suggested algorithm is compared with conventional bat algorithm (BA), PF and PSO with test conducted in different scenarios. The test result showed that LBBA has a quick response. In the event of robot abduction, the algorithm has been tested and shows fast recovery in simulated as well as in practical environment.

Table 3 discusses the experiments based on applying evolutionary approaches to basic localization techniques.

3.2. Autonomous map building

The localization strategies discussed earlier (Section 3.1) require environment map. In the most of the cases, the map is usually hand made. For self-localization, the robot utilizes different landmarks such as artificial beacons, walls etc. Therefore, to obtain accurate position, the environment map contains these landmarks. However, in large or dynamically changing environments, localization is very difficult. The configuration of the environment changes

Table 3
Evolutionary approaches for mobile robot localization.

Reference	Optimization scheme	Simulation and Experiment	Advantages	Drawbacks
Havangi (2019)	PSO	Simulation: MATLAB (2013). (Tested in simulated data as well as real world datasets). System configuration: 3 GHz Core2Duo processor-based Intel PC. Experiment: GPS based 4-wheeled vehicle with laser sensor and wheel encoders.	• The robot localization converts dynamic optimization to find the best robot pose estimate. • It does not require noise distribution. • The proposed system is efficient in terms of consistency, accuracy and computational cost.	• The encoder provides poor odometry information. • Additional errors are generated due to wheel slip and attitude errors.
Vahdat et al. (2007)	PSO and DE	Simulation: MATLAB 2006.	• The proposed system converges faster and is robust. • Due to the usage of random search operators in evolutionary methods, low SNR yield robust localization.	–
Huo et al. (2013)	DEPSO	Experiment: Up-voyager robot equipped with a laser scanner LMS291.	The proposed system inhibits the particle degeneracy and enhances the diversity, meanwhile improves the convergence speed and positioning accuracy.	–
Havangi et al. (2010)	Hybrid approach: PSO + PF	Simulation.	The developed system is more consistent than the classical systems. The experimental results show that the localization using the proposed multi swarm particle filter is more accurate than the standard Particle filter.	–
Pinto et al. (2015)	EKF + PSO	Experiment: Factory robot.	The proposed technique is accurate, flexible and robust since it achieves an error, that is lower than 0.04 m and 2°for the virtual environment, and 0.06 m and 7°under realistic scenarios.	Requires more sensory information for localizing the robot.
Dastjerdi et al. (2016)	PSO	Experiment: Soccer humanoid robots.	The proposed method has high accuracy and very resistant into the noise.	–
Mali (2015)	PSO + ACO	Simulation.	An intelligent based obstacle avoidance strategy is applied.	–
Armingol et al. (1999)	Iterative EKF + GA in ultrasonic sensor-based system.	Experiment: B21-RWI mobile robotic vehicle, equipped with 24 ultrasonic sensors.	Requires less computational time.	A priory information on locations of beacons is required to estimate the robot's position.
Wang et al. (2015)	GA-Fuzzy logic based EKF	Experiment: Two-wheeled differential drive robot.	The proposed GA-FL approach estimates the path which almost matches the actual path. The optimal filter results in very low error.	The proposed system needs to be tested in physical robot in a real environment.
Rajurkar et al. (2016)	GA based FLC	Experiment: Autonomous vehicle.	Results in effective tracking of targets in complex environment.	Efficiency of the proposed method should be tested on floors with no tracks.
Neto et al. (2019)	LBBA	Simulation: MATLAB. Experiment: P3DX robot.	The proposed method escapes from local minima in highly complex environments.	The proposed system should be tested in shared control environemt.

due to presence of dynamic objects or explicit modification. This problem is solved by automatic map building. As per this strategy: the robot starts navigating from a randomly initial point. It explores the environment autonomously thorough its sensors. Further it gains environment knowledge, builds a map through interpreting the scene. This helps the robot to localize relative to the map (Siegwart et al., 2011).

The current advances in computer vision and robotics have made this goal nearly achieved. However, the major concern is in creating and modifying the environment map automatically. In robotics, this is commonly known as the SLAM problem.

As stated earlier, localization estimates the robot position (and its path) from environment map. Mapping creates the environment's map from the information on robot's accurate path. SLAM utilizes the data collected from the robot's proprioceptive and exteroceptive sensors to recover both the environment map and robot path. The collected data are based on the displacement of robot estimated from the odometry and features such as lines, corners and planes. These features are extracted from ultrasonic sensor, laser sensor or camera images. In unknown environments, SLAM technology allows the robot to build or update maps while monitoring their places concurrently. Applications of SLAM include home applicants (lawn mower, vacuum cleaner), UAV surveillance system, mines exploration, underwater reef tracking, terrain mapping for localization in space etc.

Generally, SLAM is formulated in a probabilistic way, where the present position and robot map is estimated as a probability distribution. Objective of SLAM is to estimate the robot's location and environment map from a given series of controls and sensor observation over distinct time steps. Below, we demonstrate the mathematical formulation of SLAM.

Let us denote X_T, U_T and M as robot path, robot's relative motion sequence and environment map respectively (Siegwart et al., 2011).

$$X_T = \{x_i | 0 \le i \le T\} \tag{15}$$

$$U_T = \{u_i | 0 \le i \le T\} \tag{16}$$

$$M = \{m_i | 0 \le i \le n-1\} \tag{17}$$

In SLAM, the robot's initial location x_0 is supposed to be known. The robot motion between time $t-1$ and t is denoted by u_t. The robot is attached with a sensor reference frame. The sequence of landmark observations in this frame of reference can be defined as:

$$Z_T = \{z_i | 0 \le i \le T\} \tag{18}$$

For a camera-based robot, the observation z_i can be a vector representing the lines coordinates or corners in an image.

From the above terminology, SLAM is defined as the process of recovering a model of the map M and the robot path X_T from the odometry U_T and observations Z_T. We formulate the SLAM problem from two different perspectives: Full SLAM and Online SLAM. In Full SLAM the entire robot path is updated. However, the online SLAM updates the robot's current location only. The full SLAM problem estimates the joint posterior probability over X_T and M from the data. That is, it computes, $p(X_T, M|Z_T, U_T)$. Conversely, the online SLAM estimates the joint posterior probability over x_i and M from data, that it computes $p(x_t, M|Z_T, U_T)$. This signifies that the full SLAM problem recovers the robot's entire path X_T, while the online SLAM estimates the robot's current position x_t. Next, we discuss two important SLAM approaches utilizing the standard EKF and UKF approach.

3.2.1. EKF-SLAM based approaches

Historically, the EKF-Based SLAM is the first formulation. It was introduced in several papers (Cheein et al., 2009; Ahmad and Namerikawa, 2013; Wang et al., 2012; Burbridge et al., 2008; Kim and Oh, 2008; Erturk et al., 2012; D'Alfonso et al., 2013; Civera et al., 2008; Cheein and Toibero, 2010; Rituerto et al., 2010; Javad et al., 2017; Valiente et al., 2014). EKF SLAM uses an extended state vector containing the robot pose and the position of all the features in the map. Cheein et al. (2009) proposed an EKF-based SLAM to estimate the position and orientation of a robotic wheelchair employed in unknown environment. The suggested SLAM technique includes reconstruction of the environment map for future confirmation of secure navigation. In Ahmad and Namerikawa (2013) Ahmad et al. utilized the EKF approach for localizing a robot with intermittent measurements. The proposed approach focuses on effective location estimation in an environment where measurement data are not available. Location can be estimated even if with uncertainty in observations by mobile robot. Wang et al. (2012) proposed an improved EKF based SLAM method to estimate the robot position via omnidirectional vision system. This research uses omnidirectional vision to produce environment information around the mobile robot. This information is utilized to extract the environment feature. Finally, the landmark is located and the EKF approach is used to synchronously update the attitude and location of the robot as well as map library. The efficiency of the suggested SLAM algorithm is used to investigate x-axis and y-axis position errors.

In Burbridge et al. (2008) Burbridge et al. presents 2D SLAM implementation that uses monocular omni-directional vision. In this paper the location efficiency is evaluated by computing the RMSE of the robot's position over the entire trip. Due to known data association and four pre-initialized features, no drift error occurs. However, a drift measure must be included in the assessment when measuring efficiency in a real-world setup. The error analysis is done mostly from the perspective of number of features, measurement noise and field of view (FOV). Considering the number of features, it is obvious that, localization accuracy increases by adding more features to the world. However, the increasing number of features may decrease the improvement in accuracy. Hence, considering the FOV it is evident that the bigger the FOV, the more precise the localization accuracy. It is also observed that localization is very sensitive to noisy measurements. This is because of poor initial estimates of newly initialized characteristics. This leads to detrimental refinement in estimating the robot's location. Kim and Oh (2008) utilized the omni-directional camera to extract vertical lines. The horizontal lines are obtained from range sensor data. The robot position is estimated and a feature map is build using EKF, which uses the extracted lines features. The velocity of the robot used in this research is 0.7 m/s. The position error of the robot is estimated after travelling over 120 m.

Erturk et al. (2012) analyzed the performance of an omnidirectional EKF based visual SLAM system in a MATLAB based simulated environment unified system for automation and robot simulation (USARSim). The overall error bound of omnidirectional visual SLAM (VSLAM) and laser range finder (LRF) based SLAM is compared. Compared to LRF based SLAM, the omnidirectional VSLAM approach is proved to be more promising in terms of localization accuracy. D'Alfonso et al. (2013) suggested a segment-based SLAM algorithm using modified EKF for mobile robot localization and surrounding environment mapping. Further Civera et al. (2008) utilized direct parameterization technique for feature points within monocular SLAM. During undelayed initialization, the uncertainty is represented efficiently and accurately. Once initialized, the standard EKF prediction-update loop is used to process the features.

Cheein and Toibero (2010) proposed a hybrid scheme which combines the EKF and Monte Carlo technique. The mobile robot executing EKF SLAM procedure constructs uncertainty maps of an environment by the proposed SLAM algorithm. The navigation procedure directs the robot to region with high uncertainty defined at representative points by characterization of likelihood. Monte Carlo scheme is used to extract these points and their estimated probability by the sum of Gaussian method.

Rituerto et al. (2010) performs a comparison between EKF based visual SLAM system using conventional and omnidirectional cameras. For vision-based localization, omnidirectional camera is proved to be more appropriate due to low error. The mean of orientation and absolute estimation errors in five trajectories are also compared.

Javad et al. (2017) examines the frameworks of EKF and sigma point Kalman filter (SPKF) to enhance the precision of the estimation in SLAM. The comparison illustrates that SPKF has better performance than EKF. Further, Valiente et al. (2014) compared the performance stochastic gradient descent (SGD) and EKF algorithm implemented in a visual SLAM based robotic system. SGD is preferred to be chosen considering the effect of non-gaussian errors and non-linearities; however, in a low-noise environment, EKF method is proved to be more appropriated to provide a more accurate solution with higher convergence rate.

EKF based SLAM has the limitation in linear propagation of means and covariance and derivation of Jacobin matrices. Normally, the sensor models and vehicle are of a very high nonlinear nature. Hence filter divergence occurs, because of the effects of linearization needed in the EKF (Andrade-Cetto et al., 2005). To resolve this different UKF approaches developed (Andrade-Cetto et al., 2005; Martinez-Cantin and Castellanos, 2005; Choi et al., 2009; Schymura and Kolossa, 2018).

3.2.2. UKF-SLAM based approaches

Andrade-Cetto et al. (2005) suggested an UKF approach to reduce the linearization effects of EKF-SLAM technique. The unscented transformation (UT) proved to be better than standard EKF approach while estimating nonlinear mean and variance. Further, Martinez-Cantin and Castellanos (2005) presented an Unscented Filter based SLAM, which represents a suitable framework for the SLAM problem. The proposed approach increases State estimation accuracy (such as tighter uncertainty bounds and lower errors) over the typical EKF-based scheme. Choi et al. (2009) utilized the adaptive online method to compute measurement noise distribution (MNE) for SLAM using mean and variance. The proposed approach produces better result in comparison to typical EKF-based SLAM. (Schymura and Kolossa (2018) developed a potential field-based strategy of active exploration required for acoustic SLAM. This research performs an analysis on localization fine-error (the average localization error) and translational and rotational pose errors. The performance of the full SLAM is evaluated by translational and rotational pose error. These errors are achieved by taking the average errors between the estimated robot trajectories and ground-truth. The average computation time of the proposed method in 0.09 ms.

Different authors adopted hybrid approaches which utilizes probabilistic localization techniques in the SLAM. Fernández et al. (2014) suggested a SLAM strategy that combines the robot's internal odometry with the widespread appearance of panoramic pictures. The authors applied MCL to locate the robot. Yuen and MacDonald (2003) proposed a sequential Monte Carlo SLAM architecture. In the proposed system multiple numbers of general PFs are initialized to estimate the position of robot and obstacle simultaneously. The localization error continues to accumulate if only the odometry is used by the robot. Absolute position error of the estimated robot trajectories is analyzed. Song et al. (2018) developed a LiDAR SLAM-based control scheme with obstacle avoidance. The authors proposed Cartographer SLAM method for map building and positioning mobile robot. The localization accuracy is verified by estimating the average position error in x and y-*axis*. Basically, the robot motion technique utilizes four coordinate points positioned in the surroundings. This is regarded as the robot navigation control reference. The difference between point and robot heading angle is provided as input to the navigation controller for correcting motion error. In Caruso et al. (2015) the authors utilized omnidirectional cameras with a large-scale direct monocular SLAM scheme. Somlyai and Vámossy (2015) proposed a 3D reconstruction and map building method for mobile robots. The proposed SLAM algorithm makes use of RGB-D camera.

3.2.3. SLAM based brain-controlled robot localization

SLAM is found to be powerful technique for localizing brain-controlled mobile robots in unknown environments. Different authors adopt hybrid strategies, which combines SLAM with other techniques, for estimating robot position. Li et al. (2018) proposed an effective brain-robot interface (BRI) system implementing the SLAM model to navigate and control mobile robots in unknown environments. The human EEG signal is recorded by 40 channels based digital EEG recoding system (NuAmps-NeuroScan). The motor imagery (MI) analyzes this signal through the common spatial pattern (CSP)-based support vector machine (SVM) classification technique. The proposed SLAM scheme focuses on improved RGB-D SLAM which combines feature tracking (based on optical flow) and deep learning techniques. The proposed methods get speedup by optical flow strategy and object identification based on deep learning provides higher accuracy, stronger robustness, and additional environmental information simultaneously. Human operator manipulates the robot through the BRI based on MI combined with SVM classification based on CSP. The suggested methodology locates the robot more correctly by removing the error of pose calculated from ordinary matching of features.

Yuan et al. (2019) suggested a FastSLAM algorithm which involves in assisting the mobile robot to get positioned accurately. Apart from localization, this approach also focuses to build the environment map. This algorithm utilizes the generic PF in estimating the position of robot. The proposed visual-based SLAM scheme provides precise positioning to the robot with uncertainties in sensor reading, the random changes in light intensity, and having limited information about the RGB landmark. The paper adopts probability potential field (PPF) method (an effective dynamic obstacle avoidance scheme), which is involved in predicting the obstacles future location from their motion analysis. The PPF method is used to generate obstacle-free path. This helps the robot to apply dynamic collision avoidance approach for smooth navigation. The proposed brain-controlled system consists of an EEG recording device named NeuroScan, an Intel core-7 processor based central computer, a mobile robot, and the operator.

Yuan et al. (2018) proposed a control strategy involved with brain-teleoperation. This technique adopts deep learning methods to navigate and control the mobile robot. This methodology is well suited in unknown environments. The robot controlled is mostly influenced by a steady state visually evoked potentials (SSVEP) based BCI system and deep learning. The human intentions are recorded as EEG signals by NuAmps device. The online SVM classifier analyzes EEG signals and decodes them to generate movement intentions which results in providing motion commands to control the robot. A collision-free path is planned by adopting artificial potential field (APF) method. The adopted SLAM process obtains surrounding information. Finally, the map is stored as global metric.

Liu et al. (2018) developed a brain-machine interface (BMI) based on SSVEP. The recorded EEG signals get classified by canonical correlation analysis (CCA) algorithm. The processed signal is translated to motion commands for planning an APF based trajectory. PF-based SLAM is combined with EEG-APF for obstacle-free navigation of robot to the defined goal point. In the proposed system, major involvement of SLAM approach is building the corridor's global map. The EEG-APF approach plans an obstacle-free trajectory. Apart from above various authors adopt other SLAM based schemes such as RatSLAM (Müller et al., 2014), MonoSLAM (Davison et al., 2007), OpenRatSLAM (Ball et al., 2013) etc. for localizing mobile robots.

Table 4 displays the simulations and experiments conducted by different authors using SLAM based localization approach.

3.2.4. Evolutionary-SLAM based approaches

Jajulwar and Deshmukh (2015) developed a PSO based adaptive tracking controller for mobile robot navigation. This controller generates optimal collision-free paths and SLAM takes care of localization and updating the map. Chang et al. (2016) addressed an improved PSO based resampling method to address the particle deletion problem occurred in standard FastSLAM technique. The simulation result proves that accuracy of FastSLAM is improved by adopting PSO-based approach. Compared to conventional FastSLAM, this approach produces smaller error in estimating both the robot pose and features. In Low et al. (2010), Low et al. developed a modified version of PSO for VSLAM system. The scheme uses visual odometry to predict the robot's position and orientation. Electronic compass installed on the board is used for obtaining the robot orientation. The proposed mapping system applies modified PSO for building geometrical maps (feature-based). The proposed system processes the features recorded from camera sensor and optimizes them with PSO which results in low error rate. This results in estimating feature locations and robot's position and orientation jointly.

Mohamed et al. (2011) proposed a mathematical model for an autonomous mobile robot using VSLAM and intelligence-based path planner using PSO. Further, Matsuo and Miura (2012) developed an efficient algorithm for solving issues involved in using hand-drawn maps for mobile robot navigation. The hand-drawn maps suffer from different limitations like incorrect position/size estimation, object missing etc. This results in difficulty to map sensory data with objects in map. To solve this problem, the proposed system combines FastSLAM with PSO to refine the map and generate accurate information. This approach is implemented in real scenario in stereo-based localization in outdoor environment.

Ankışhan et al. (2013) proposed an improved FastSLAM technique named PSO passive congregation (PSO-PC) for robot's position estimation. This method optimizes particle samples in the sample phage. It is combined with square root unscented (sru) KF approach for predicting or updating the robot's position. The proposed localization system performs a comparison among UFastSLAM, SruFastSLAM, FastSLAM II and SruPSOFastSLAM. Based on the MSE and heading angle, SruPsoFastSLAM produces better result in terms of MSE and heading angle. Havangi et al. (2014) utilized SRUFastSLAM method using less particles to estimate SLAM

Table 4
SLAM based localization techniques.

Reference	Approach	Simulation and Experiment
Wang et al. (2012)	Omni-VSLAM	Experiment: Tracked mobile robot.
Burbridge et al. (2008)	Monocular omnidirectional SLAM	Experiment: Robot with vision tracking system.
Kim and Oh (2008)	EKF-VSLAM	Experiment: MORIS robot.
Erturk et al. (2012)	Omni-VSLAM	Simulation: MATLAB and USARSim. Experiment: Pioneer P2AT robots used in USARSim.
D'Alfonso et al. (2013)	Segment based SLAM	Experiment: Khepera III robot.
Civera et al. (2008)	Monocular SLAM	Simulation-1: MATLAB. Simulation-2: C++. Total five experiments conducted.
Cheein and Toibero (2010)	EKF + Monte Carlo rule	Experiment: Pioneer 3AT mobile robot (A non-holonomic unicycle type mobile robot).
Rituerto et al. (2010)	EKF -Visual SLAM	Experiment: Robot with hyper-catadioptric and conventional cameras.
Cheein et al. (2009)	EKF-SLAM	Experiment: Autonomous robotic wheelchair.
Ahmad and Namerikawa (2013)	EKF based localization.	Experiment: E-puck robot which transmits data to the processor via a Bluetooth device.
Javad et al. (2017)	EKF vs. SPKF	Simulation: MATLAB.
Valiente et al. (2014)	EKF vs. SGD	Experiment: Pioneer P3-AT indoor robot equipped with a hyperbolic mirror and a firewire camera (1280 × 960) to generate the omnidirectional image.
Andrade-Cetto et al. (2005)	UKF-SLAM	Simulation: Mathematical analysis.
Martinez-Cantin and Castellanos (2005)	Unscented SLAM	Simulation: Simulated on Dataset. Experiment: Vehicle travelling in a rectangular-shaped trajectory.
Choi et al. (2009)	MNE SLAM	Simulation: MATLAB.
Schymura and Kolossa (2018))	UKF based Acoustic SLAM	Simulation: In reverberant acoustic scenarios. Experiment: MATLAB (Processor: Intel Core i5, RAM: 16 GB, Operating system: Ubuntu).
Fernández et al. (2014)	MCL-based Hybrid metric-topological SLAM	Experiment: Pioneer P3-AT robot equipped a catadioptric vision system (to capture omni-directional images).
Yuen and MacDonald (2003))	MCL-based SLAM	Simulation: C++ with STL.
Song et al. (2018)	LiDAR SLAM with MCL framework	Experiment: Wheeled mobile robot.
Caruso et al. (2015)	Direct monocular SLAM	–
Somlyai and Vámossy (2015)	SLAM with RGB-D camera.	Simulation: In desktop computer with Intel Core 2 Quad 2.66 GHz processor, and 8 GB RAM.
Li et al. (2018)	Improved RGB-D SLAM	Experiment: Robot with RGB-D sensor.
Müller et al. (2014)	RatSLAM	Experiment: The NAO Humanoid robot equipped with cameras having HOR: 60.9° and VER: 47 0.6° positioned in its head. The robot is also equipped with fourteen joint motors which offer 25 degree of freedom (DOF)s for flexible movements.
Davison et al. (2007)	MonoSLAM	Experiment: Humanoid robot HRP-2.
Ball et al. (2013)	OpenRatSLAM	Experiment: iRat Robot.
Yuan et al. (2019)	FastSLAM	Experiment: Mobile robot equipped with laser sensor and visual sensor (Xtion Pro live camera (by ASUS)).
Yuan et al. (2018)	KF SLAM	Experiment: Wheeled mobile robot.
Liu et al. (2018)	PF SLAM	Experiment: Mobile robot with SICK laser sensor, odometer and a Kinect sensor.

accuracy. The proposed method uses PSO for proposal distribution. The comparative results of SRU-FastSLAM and unscented FastSLAM (UFastSLAM) demonstrate that, SRUFastSLAM is more consistent than UFastSLAM.

Milford and Wyeth (2010) presented a biologically inspired visual SLAM system for robot involved in deliveries at office environment over a period of two-weeks. The proposed approach adopts SLAM during interaction with local and global navigation system as well as a task selection unit. Janah and Fujimoto (2018) presents a comparison between Firefly Algorithm (FA) and PSO based SLAM approach. FA is a nature inspired technique developed by studying behavior of fireflies. The comparison result shows that in general scenarios, PSO exceeds FA for solving SLAM problems. Table 5 highlights the experiments based on evolutionary SLAM approaches.

Fig. 5 represents the percentage of papers on SLAM based mobile robot localization techniques.

3.3. RFID approach

Presently, there are different approaches that uses very small low-cost RFID tags (Shirehjini et al., 2012; Panigrahi and Tripathy, 2015a, 2015b; Hahnel et al., 2004; Park and Hashimoto, 2009a, 2009b; Choi and Lee, 2009; Choi et al., 2011, 2012b; Hsu et al., 2013; Mi and Takahashi, 2015a, 2015b; Martinelli, 2015; Amri et al., 2015; Wang and Takahashi, 2016; Pöpperl et al., 2016; Xue, 2016; Hwang et al., 2017; Sudantha et al., 2017; Motroni et al., 2018a, 2018b; Yang et al., 2018; Zhang et al., 2018; DiGiampaolo and Martinelli, 2018; Wu et al., 2019). These tags are well known for their success in context-aware applications. The RFID tags are broadly classified into two categories: active and passive. Because of non-battery requirement to maintain the wake-and-query cycle, the passive RFID tags have no lifetime limit. However, active tags use battery (Shirehjini et al., 2012). To localize a robot, set of tags are arranged in a grid pattern. The robot consists of a RFID reader and an antenna (transponder). Normally, the RFID tags contains the location information. When the robot passes over a tag, the RFID reader attached to the robot detects the tag and extracts the position information (Panigrahi and Tripathy, 2015a).

Hahnel et al. (2004) proposed a probabilistic measurement model for RFID readers that make it possible to locate RFID tags

Table 5
Evolutionary approaches applied to SLAM.

Reference	Optimization scheme	Simulation and Experiment
Jajulwar and Deshmukh (2015)	PSO-SLAM	Simulation.
Chang et al. (2016)	PSO based FastSLAM	Simulation: FastSLAM simulator.
Janah and Fujimoto (2018)	Firefly vs. PSO based SLAM	Experiment: iRobot Roomba 600 equipped with UTM-30LX (2D LRF).
Low et al. (2010)	Modified PSO based VSLAM	Simulation: MATLAB.
Mohamed et al. (2011)	PSO based VSLAM	Simulation: MATLAB.
Matsuo and Miura (2012)	PSO based FastSLAM	Simulation.
Ankışhan et al. (2013)	SruPSO-FastSLAM	Simulation.
Havangi et al. (2014)	PSO based SRU-FastSLAM	Simulation: Victoria and Car Park data sets.
Milford and Wyeth (2010)	RatSLAM	Experiment: Pioneer 3 DX robot equipped with a panoramic imaging system.

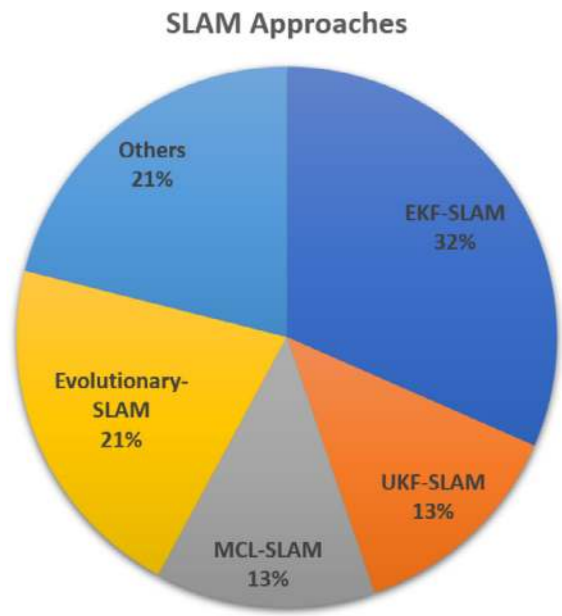

Fig. 5. Percentage of papers on SLAM based localization.

accurately in the surrounding. The proposed system uses a laser range sensor to learn the environment's geometric structure using FastSLAM algorithm. Next, the position of the tags is estimated based on robot's path. The authors applied MCL to determine the robot's location globally. In this research, localization error with and without odometry during global localization with RFID tags is analyzed. Further laser-based global localization error with and without RFID data is compared. However, in Park and Hashimoto (2009a) used read-time model of IC tags to decrease the error of localization without using external sensors or vision-based system. The proposed RFID system uses a circular antenna which detects IC tags with a frequency band of 13.56 MHz. In real time, to calculate the location and orientation of the robot, the suggested localization technique applies average operation over detected IC tag coordinates i.e. (x, y) positions. Each tag sends a serial number in relation to its absolute position information that is stored in the robot database. The IC tag is identified only when it found in the reception range of the antenna for more than 50 μs. The effectiveness of the suggested technique is examined by conducting experiment on robots navigating in indoor environment. The analysis on the recorded trajectories proves that, localization error can be decreased to modify the position of the robot without using external sensors or a vision system. The suggested strategy is well adapted to use for the elderly and disabled in hospitals or nursing facilities.

Trigonometric functions were used by Park and Hashimoto (2009b) to predict robot pose using passive RFID system. The robot's position is estimated from the information on positioning of IC tags and angle of incidence for these tags. The suggested technique decreases position error using these functions and IC tag cartesian coordinates in a regular distribution. The error in x-axis becomes bigger when the robot turns left-to-right, and vice-versa in a broader manner. This makes the error in y-axis comparatively lower than the error in x-axis. The suggested system identifies the IC tags even with any wear, dirt, vibration or cover. It is therefore proven that the IC-tagged-room is a viable alternative for real-life apps.

Choi and Lee (2009) and Choi et al. (2011) suggested a fusion sensor scheme to remove robot location uncertainty using ultrasonic sensor distance measurements. The hybrid strategy suggested for efficient robot localization combines global position estimation (GPE) (a RFID scheme) and local environment cognition (LEC) (ultra-sonic sensor-based system). Robot position is estimated by matching the data recorded from local environment map and the global position. Analysis is based on the IC tag gap of 0.3 m and 0.5 m.

Shirehjini et al. (2012) utilizes the passive RFID technology to estimate the position and orientation of mobile objects. The developed system requires RFID tags to be mounted on PVC isolation foil-based carpet pads. The tags are placed at (X; Y) position in an equidimensional $N \times M$ carpet pad, where X and Y correspond to the row and column of the carpet pad, such that N; $M > 1$ and X; $Y > 1$. Each mobile object is mounted with an RFID reader. The software module computes the object position depending on the data tuple < M, N, X, Y>, the RFID tag's ID, and the timestamp based on the information scanned from the RFID tag closed to the specific reader. Compared with previous research and performing a series of experiments, the proposed localization approach is proved to be more effective due to low average error to place and orient indoor object. Choi et al. (2012b) utilized the passive RFID based positioning method dealing with ultra-high frequency (UHF) for cost efficient localization and tracking of UAV. Hsu et al. (2013) applied average function to a set of detected tags for estimating robot's position.

Panigrahi and Tripathy (2015b) proposed a simulated model for planning shortest path, where the robot position can be obtained from RFID tags arranged in equidistance manner in grid constructed surroundings. Mi and Takahashi (2015a) proposed a new likelihood function to detect tag for MCL with large size RFID reader antenna and a smaller number of RFID readers. This approach results in increase of self-localization performance by which the installation cost of ID tag is reduced. Estimation error of the RFID system with 20 and 5 RFID readers are evaluated. Compared to 20 RFID readers the 5-reader system is acceptable even if

Table 6
Analysis of existing RFID based robot localization schemes.

Reference	Approach	Application	Sensors	Simulation and Experiment
Shirehjini et al. (2012)	AMI	Indoor	–	Experiment: Mobile stand.
Panigrahi and Tripathy (2015b)	Graph based	Indoor	Ultrasonic	Simulation: Matlab-R2009a.
Motroni et al., (2018a)	SAR	Indoor (warehouse)	14 Prime13 smart cameras. *Camera system sampling frequency*: 120 Hz.	Experiment: Wheeled mobile robot.
Motroni et al. (2018b)	Extended SAR	Indoor	IMU, LRF data, sonar and eight Vicon MX calibrated cameras.	Experiment: Pioneer 3-AT (UGV).
Yang et al. (2018)	KF + HIMR	1D moving object	RF sensor	Experiment: Robotic Arm.
Mi and Takahashi (2015a)	MCL	Indoor	–	Experiment: Omni-directional mobile robot.
Mi and Takahashi (2015b)	MCL	Indoor	–	Experiment: Omni-directional vehicle.
Zhang et al. (2018)	BFVP	Indoor (retail environment)	Lidar and Microsoft Kinec.	Experiment: Wheeled robot with two Raspberry Pi 3 controllers on the round robot base REX-16D from Zagros robotics.
Martinelli (2015)	EKF and UKF	Indoor	IR sensor	Experiment: Unicycle-like robot with a differential drive kinematics.
Wang and Takahashi (2016)	PF	Indoor	–	Experiment: Omni-directional vehicle.
DiGiampaolo and Martinelli (2018)	KF	Indoor (warehouse)	–	Experiment: Unicycle-like robot.
Pöpperl et al. (2016)	Polarimetric filter	Indoor (warehouse and industries)	–	Experiment: Wheeled mobile robot.
Wu et al. (2019)	UWPP	Indoor (Warehouse)	–	Experiment: Arm like robot.
Park and Hashimoto (2009a)	Trigonometric functions	Indoor navigation for disabled people.	Distance and touch sensors (bumper switches)	Experiment: Ubiquitous Robot (UBIRO).
Park and Hashimoto (2009b)	Trigonometric functions	Indoor navigation for elderly and disabled people.	–	Experiment: UBIRO based on an electric wheelchair (EMC-230)
Choi et al. (2012b)	UHF-RFID approach	Indoor localization and tracking.	Ultra-sound sensor	Experiment: GAORI (A tricopter type UAV).
Hahnel et al. (2004)	MCL ++ FastSLAM	Indoor	Laser range scanner	Experiment: Pioneer 2 robot.
Choi and Lee (2009) and Choi et al. (2011)	Sensor fusion and Hierarchical localization (GPE + LEC)	Indoor	9 ultrasonic sensors (HRC01). *Measuring range*: 6 m.	Experiment: FiBot (Car type robot). *Size*: 300 mm × 300 mm
Hsu et al. (2013)	Average function on detected tags.	Indoor	–	Experiment: Mobile Robot car manufactured by HANBACK ELECTRONICS.
Hwang et al. (2017)	Neural-Network	Indoor (Human localization via AGV)	–	Experiment: AGV robot.
Amri et al. (2015)	Multi-modal data fusion	Indoor (Home environment)	Pyroelectric Infra-Red (PIR), RFID and sound sensors. *PIR Range*: 6 m × 4 m	Simulation: Matlab System configuration: Intel(R) PC configured with Core i7-3540 M processor (500 s CPU time).
Sudantha et al. (2017)	Vision-based approach	Indoor	Camera sensor (5 megapixel). Captured image size: 2592 × 1944 image.	Experiment: Robot equipped with a raspberry Pi microcontroller.

Table 7
Analysis on existing RFID systems.

Reference	RFID Reader	RFID Reader Specification	Band	Frequency	Number of RFID readers	RFID Antenna
Shirehjini et al. (2012)	Mifare QC-3100-AT RFID reader	Standard: ISO 15693.	HF	–	4	–
Motroni et al., (2018a)	Impinj Speedway Revolution R420 UHF-RFID reader.	Signal transmission power: 27 *dBm*.	UHF	865.7 MHz (ETSI Channel 4).	1	UHF-RFID CAEN antenna (WANTENNA X019). *Detection range*: 37 tags (in trajectory).
Motroni et al. (2018b)	Impinj Speedway Revolution R420 UHF-RFID reader.	Reader input power: 27 *dBm*. *Reader provides*: phase of the tag backscattered signal, RSSI, tag EPC, reading time stamp, index of tag detecting antenna.	UHF	865.7 MHz (ETSI Channel 4).	1	WANTENNAX019 and WANTENNAX007. *Polarization*: circular.
Yang et al. (2018)	Basic RFID reader.	–	–	–	1	–
Mi and Takahashi (2015a)	Basic RFID reader.	*RFID reader size*: 60 × 60 [in mm] (20 reader system). 120 × 120 [in mm] (5 reader system).	HF	–	20, 5	–
Mi and Takahashi (2015b)	Basic RFID reader.	–	–	–	24	–
Zhang et al. (2018)	ZEBRA FX9500 fixed RFID reader.	*RF transmission Power*: maximum 33 *dBm*. *Protocol*: EPC Gen2	UHF	902 MHz – 928 MHz band.	1	Four ZEBRA AN720 RFID antennas. *Gain*: 6 *dB*. *Polarization*: circular.
Martinelli (2015)	M6e ThingMagic RFID reader.	–	UHF	868 MHz.	1	–
Wang and Takahashi (2016)	Basic RFID reader.	–	HF	–	8	Large antenna.
DiGiampaolo and Martinelli (2018)	Trimble M6e RFID reader.	*Reader input power*: 24 *dBm*.	UHF	867 MHz	1	*Polarization*: Circular. *Gain*: 6 *dB*.
Pöpperl et al. (2016)	UWB FMCW RFID reader.	*Size*: 112 × 95 [in mm]. *Signal bandwidth*: 1.25 GHz. *Power consumption*: 3.0 W	SHF	7.875 GHz	1	*Gain*: 25 *dBi*.
Wu et al. (2019)	Impinj Speedway R420 reader and ThingMagic M6e reader.	*Standard*: ISO 18000-6C protocol. *Protocol*: Impinj Speedway R420 reader supports EPC Gen2 protocol.	UHF	Between 920.5 MHz and 924.5 MHz (for Impinj Speedway R420).	2	MTI based antenna: MT- 262,024 with wireless edge. *Size*: 190 × 190 × 25 [in mm] *Polarization*: Circular. *Gain*: 7.5 *dBic*.
Park and Hashimoto (2009a)	S6350 Midrange Reader Module (Texas instruments).	Compatible with all ISO 15,693 devices.	HF	13.56 MHz.	1	Circular antenna. *Tag detection range*: 170 mm from center of antenna.
Park and Hashimoto (2009b)	S6350 Midrange Reader Module (Texas instruments).	Compatible with all ISO 15,693 devices.	HF	13.56 MHz.	1	Circular antenna.
Choi et al. (2012b)	Mono-static UHF readers.	–	UHF	–	–	Mono-static UHF antennas.
Hahnel et al. (2004)	RFID reader (by Alien Technology).	–	UHF	915 MHz.	1	Two antennas. *Polarization*: Circular.
Choi and Lee (2009) and Choi et al. (2011)	KISR300H RFID reader.	–	HF	13.56 MHz.	1	KISR300H RFID antenna. *Antenna Size*: 150 mm × 150 mm.
Hsu et al. (2013)	HBE-FRID-RX series RFID reader (HANBACK ELECTRONICS).	–	UHF	900 MHz.	1	HBE-FRID-RX series RFID antenna (HANBACK ELECTRONICS).
Hwang et al. (2017)	RM300 UHF reader module.	–	UHF	–	1	Two perpendicular antennas.

it produces higher estimation error. This is because; the 5-reader system is well suited for self-localization by the autonomous robot in indoor environment.

As addressed in Mi and Takahashi (2015b), authors applied MCL in RFID based system with fewer RFID readers and IC tags with lower density. An efficient particle reinitializing method is proposed to improve self-localization. The system attains stable location state and self-localization is usually accurate and stable. By applying distinct probability features to the RFID scheme, the self-localization is optimized. The performance of self-localization is analyzed with the configuration of 96 and 24 RFID reader system from the prospect of three different models. The analysis on mean, max and orientation error on the above two RFID reader systems proves that, with 24 RFID readers and reduced number of IC tag textiles on the floor, MCL-based self-localization works properly for a realistic situation. This reduces cost compared to 96 RFID readers considerably.

Martinelli (2015) developed a RFID based global indoor localization unit with received signal strength indication (RSSI). The proposed system includes UHF-RFID signals having phase shift. This

Table 8
Analysis on different IC tags used in RFID based robot localization systems.

Reference	Tag type	Tag size (in mm)	Specification	Tag Arrangement
Shirehjini et al. (2012)	Passive	85 × 55	Tag-it HF-I transponders (by Texas Instruments).	Checkerboard, 39 tags/carpet pad.
Motroni et al., (2018a)	Passive	–	*IC tags based on*: MZ-4 chip: [LAB ID UH3D40], MZ-5 chip: [LAB ID UH331], MZ-6 chip: [LAB ID UH106, Easy RFID Clepsidra, Easy RFID Fashion and Smartrac DogBone] and NXP UCODE-7 chip: [Easy RFID Garbage].	Deployed on floor, 54 tags/ 40 m^2.
Motroni et al. (2018b)	Passive	–	Monza R6 chip. *Sensitivity*: −22.1 *dBm*.	Installed on floor, 38 tags/ 52.5 m^3.
Yang et al. (2018)	Passive	–	Backscatter tag.	Mounted to robot.
Mi and Takahashi (2015a)	Passive	–	–	*Test-1*: Lattice 25 tags/m^2 *Test-2*: Hexagon, 24 tags/m^2.
Mi and Takahashi (2015b)	Passive	10 × 20		Square pattern, 100 tags/m^2.
Zhang et al. (2018)	Passive	–	Avery Dennison AD-237. *Read wake-up sensitivity*: −22.1 *dBm*. *Write wake-up sensitivity*: −18.8 *dBm*.	Random distribution, 674 tags/ 204 m^2.
Martinelli (2015)	Passive	–	–	Grid-pattern (ceiling), 1 tag/m^2.
Wang and Takahashi (2016)	Passive	–	–	Installed on the floor, 100 tags/ m^2.
DiGiampaolo and Martinelli (2018)	Passive	–	*Antenna*: Inlay tag LAB-ID UH105. *Polarization*: Linear.	Deployed in shelves, 4 tags/m^2.
Pöpperl et al. (2016)	Passive	72 × 77	Chip less TDR RFID Tag. *Antenna polarization*: Configurable.*Data capacity*: 9 bits. *Gain of antenna*: 12 *dBi*. *Symbols*: 3. *Modulation*: 8-PSK. *Overall loss* (*theoretic*): 8.48 *dB*.	Installed in laboratory.
Wu et al. (2019)	Static passive	–	COTS UHF Gen 2-compliant tag (Alien 9640). *Polarization*: Linear.	Attached to object.
Park and Hashimoto (2009a)	Passive (198 tags) *Tag spacing*: 34 cm	–	–	Grid-pattern.
Park and Hashimoto (2009b)	Passive (198 tags) *Tag spacing*: 34 cm	76(W) × 45(D) × 0.23(H)	–	Grid-pattern, 9 tags/m^2.
Choi et al. (2012b)	Passive (n tags)	–	–	Deployed on floor.
Hahnel et al. (2004)	Passive (100 tags)	110 × 50	–	Grid-pattern, 8 tags/m^2 (apx.).
Fernández et al. (2014)	Passive	30 × 30	–	Rectangular grid-pattern, 9 tags/m^2.
Yuen and MacDonald (2003)	Passive	30 × 30	–	Grid-pattern, 9 tags/m^2.
Hsu et al. (2013)	Passive	–	–	Cartesian grid, 16 tags/m^2.
Hwang et al. (2017)	Passive	–	–	3 tags mounted on triangular apparatus.

system uses multi-hypothesis unscented and EKF to localize mobile robot and to improve co-ordinate estimation of RFID tags. The robot's RFID reader is responsible for measuring phase shift of UHF-RFID signals and RSSI. The localization system requires initial information on the IC tags positions with error tolerance up to 1 m. The analysis on position estimation error by experimenting with different test cases proves the efficiency of the proposed algorithm. Amri et al. (2015) suggested a data fusion (multi-modal) localization approach suitable for indoor navigation using a set-membership method. The proposed algorithm permits error bounded of ±250 mm on each distance measured. Moreover, this system uses three RFID antennas.

Wang and Takahashi (2016) proposed an effective localization scheme with independent PFs for landmark mapping and self-localization. This is applied to the multiple tags system and multiple RFID readers in an omni-directional vehicle. This research analyses the estimated errors from the perspective of mean and max error. Pöpperl et al. (2016) suggested a notion for wireless placement based on time domain reflectometry (TDR) chips less RFID tags. This system, utilizes polarimetric filter to reduce the distortion caused by multipath propagation. The UWB reader used in the propose system provides a decent distance resolution and a polarimetric filter efficiently suppresses multipath, which results in a substantial enhancement in the placement and decoding of the tag. In the response signals, multipath propagation is obvious. In this scenario, the tag caused a polarization shift, although overall level of the multipath signals is lowered. The combination of polarimetric adaptive filter and measurements can considerably enhance the tag response. The filtered response causes the tags to be localized with reduced mean-square-error.

Xue (2016) developed an activity theory (AT) based intelligent technique to track the state of object. This is achieved through people's behavior, activity along with movement trajectory. Hwang et al. (2017) applied a novel neural network-based model in RFID system. This research presents an analysis on average position errors in static and dynamic environment. In dynamic environment, for the longer range between the person and the vehicle, the estimated error may be large. However, the estimation errors

Table 9
Analysis on different localization techniques on RFID system.

Reference	Approach	Advantages	Drawbacks
Shirehjini et al. (2012)	AMI	Proposed system results in a low average positioning error.	The proposed RFID based localization is applied on objects with small distance to the floor.
Panigrahi and Tripathy (2015b)	Graph based	An effective system for indoor environment.	Should be tested in real environment with physical robot.
Motroni et al., (2018a)	SAR	The proposed system results in high localization accuracy.	The UHF-RFID system is not tested in indoor SLAM setting.
Motroni et al. (2018b)	Extended SAR	The proposed methodology efficiently solves the ambiguity in the tag position estimate	–
Yang et al. (2018)	KF + HIMR	The proposed Heterogeneous RFID systems achieve high accuracy with low estimation error typically 5 mm rms.	––––
Mi and Takahashi (2015a)	MCL	The proposed system efficiently localizes the robot with less RFID readers and lower density RFID tags.	The RFID system needs to be tested in real environment.
Zhang et al. (2018)	BFVP	The RFID based indoor localization exhibits very less localization error typically<0.5-m in retail environment.	–
Martinelli (2015)	EKF and UKF	The proposed system effectively utilizes EKF and UKF for tag detection and applying SLAM extend the localization accuracy.	–
Wang and Takahashi (2016)	PF	In comparison to FastSLAM, the proposed method outperforms.	–
Park and Hashimoto (2009a)	Trigonometric functions	The proposed RFID based robotic system is suitable for hospitals or nursing facilities for elderly and disabled people.	The design of the robot's front wheel needs to be improved for precise motion control.
Choi et al. (2012b)	UHF-RFID approach	The proposed system results in cost effective UAV tracking and localization.	The proposed system needs to be tested in indoor target searching, especially in public protection and security application.
Hsu et al. (2013)	Average function on detected tags.	The RFID system improves power consumption in real cruise.	In real time navigation, with presence of too much relay points, it causes a lot of time waste and power consumption.
Hwang et al. (2017)	Neural-Network	The proposed system takes help from a trained localization model and generates high localization accuracy.	–
Sudantha et al. (2017)	Vision-based approach	The proposed dynamic navigation system for mobile robots results in high localization accuracy.	The system needs to be implemented and tested in real environment.

for the static case and the dynamic case are similar in the presence of human interference. Sudantha et al. (2017) presented a vision-based approach along with Hough transformation (for line detection) for robot localization in RFID based environment.

Motroni et al. (2018a) developed a robotic system to identify items mounted by passive transponders. The authors utilize the RFID reader based on UHF to locate stationary tags. In this research, the indoor robot trajectory is measured by a calibrated vision-based system. The proposed approach uses various tags to verify whether the efficiency of the suggested strategy is independent of tag categories. It utilizes a calibrated vision-based system to evaluate localization accuracy for locating the detected IC tags. The efficiency of the suggested strategy is analyzed by different trajectories and tags. Furthermore, to guarantee high localization precision, the main features of the adopted matching feature were studied.

Further, in Motroni et al. (2018b), the authors used multiple antennas for locating static tags. These tags are tracked by two circularly polarized UHF-RFID reader antennas attached to an unmanned grounded vehicle (UGV). The suggested technique estimates the reader antenna's instant position. This is fed as input to the synthetic aperture radar (SAR) algorithm. Due to reduced localization error, the suggested method is appropriate for indoor navigation even in severe multipath environments with no propagation channel data.

Different authors proposed hybrid systems by applying KF, MCL, vision, Bayesian & PF on RFID based system. Yang et al. (2018) suggested a KF-based localization technique applied to the output of inertial microwave reflectometry (HIMR) algorithm (a linear estimator for location & tracking). Adding a KF to the original HIMR method decreases estimation error to a greater extent. Zhang et al. (2018) proposed a reliable localization algorithm named Bayesian filter of variable RF transmission power (BFVP) that enables a robot equipped with commercial off-the-shelf (COTS) RFID in providing specific location to UHF based passive RFID tags in a retail environment. The analysis on localization error shows that the suggested strategy is applied in real retail environment with considerable multi-path fading (RF signal reflection). Moreover, the error of localization is reduced by decreasing the power of RFID reader. The localization precision offers a high practical implementation value specifically to locate items in retail environment. DiGiampaolo and Martinelli (2018) developed a two-step localization system having RFID to localize objects on shelves. The suggested scheme results in a reduced average position estimation error in case of cluttered metallic racks. However, for stacked cartons, it can be reduced to few millimeters.

Wu et al. (2019) suggested a new RFID localization method with UHF to estimate the location of static passive tag using a mobile RFID antenna. The proposed system developed a novel unwrapped phase position (UWPP) model. The proposed localization algorithm is implemented on a DELL PC (32-bit) with 4 GB memory and Intel Core i3 M380 (2.53 GHz) processor. The suggested method is inexpensive in computing costs compared to the current grid-based techniques. A comparative analysis on localization error in different dimensions is performed.

Table 6 presents an analysis on RFID based localization schemes. Detailed specification of RFID system with frequency bands such as HF, UHF, SHF (super high frequency) is presented in Tables 7 and 8 addresses IC tag distribution. Table 9 addresses the merits and issues involved in different RFID based localization systems.

4. Analysis on position and orientation error

Different authors present various strategies to estimate position and orientation error of mobile robot. The position error is the difference between the robot's real position and its calculated position. Orientation error is calculated as the modulus of the difference between actual and computed orientation (Esteves et al., 2006). Localization error occurs due to the long processing time

Table 10
Comparative analysis on mobile robot localization algorithms based on error estimation and localization.

Reference	Estimated error details
Gutmann and Schlegel (1996)	Position error: 1300 mm and Orientation error: 2.5°.
Klaess et al. (2012)	*Static environment*: Distance error < 200 mm and Angular error < 9.16°.
	Dynamic environment: Distance error: [Pose tracking < 500 mm and after global localization < 250 mm].
Shirehjini et al. (2012)	*Positioning measurement*: Error: 65 mm and standard deviation: 45 mm.
	Orientation measurement: Error: 1.9° and standard deviation: 2.5°.
Motroni et al., (2018a)	Localization error < 10 mm.
Motroni et al. (2018b)	Localization error < 10 mm.
Yang et al. (2018)	Localization error: around 5 mm rms.
Mi and Takahashi (2015a)	*With 20 RFID readers*: Localization error < 10 mm and orientation error < 3.43°.
	With 5 RFID readers: Localization error < 20 mm and orientation error < 8.59°.
Mi and Takahashi (2015b)	*In 24 RFID reader system*: [Position error < 10 mm].
Zhang et al. (2018)	Localization error: 500 mm [position error: 30 mm and orientation error: 7°].
Martinelli (2015)	Error tolerance: up to 1000 mm.
Wang and Takahashi (2016)	*Simulation*: Average position error: x-axis: 8 mm and y-axis: 7 mm. Orientation error: 0.28° (apx.).
	Real experiment: Average position error: x-axis: 11 mm and y-axis: 20 mm. Orientation error: 2.46° (apx.).
DiGiampaolo and Martinelli (2018)	Position estimation error: 100 mm.
Pöpperl et al. (2016)	Mean-square-error: 21 mm.
Wu et al. (2019)	Median location error: x-axis: 20.5 mm, y-axis: 93.6 mm and 99.6 mm [combined dimension].
Park and Hashimoto (2009a)	Localization error: x-axis: 60 mm and y-axis: 53 mm.
Park and Hashimoto (2009b)	Localization error: x-axis: 133 mm and y-axis: 57 mm.
Hahnel et al. (2004)	Localization error < 2000 mm (at time step 40).
Choi and Lee (2009) and Choi et al. (2011)	*Tag gap 0.3 m*: Average error: 15.8 mm.
	Tag gap 0.5 m: Average error: 24.2 mm (Fernández et al., 2014), position error: 27 mm and orientation error: 7.04° (Yuen and MacDonald, 2003).
Hwang et al. (2017))	*With respect to AGV*:
	Average position error (static case) < 220 mm and average position error (dynamic case) < 230 mm.
Havangi (2019)	Robot position error RMSE < 0.2.
Huo et al. (2013)	*With 500 particles*: [Average positioning error: 80.442 mm and Average angle error: 7.47].
	With 1000 particles: [Average positioning error: 76.345 mm and Average angle error: 7.16].
	With 2000 particles: [Average positioning error: 75.394 mm and Average angle error: 6.74].
Pinto et al. (2015)	In virtual scenario: [Position error < 0.04 m and orientation error < 2°].
	In realistic condition: [Position error < 0.06 m and orientation error < 7°].
Dastjerdi et al. (2016)	Average position error: [112.3 mm and average angle error: 6.25°].
Armingol et al. (1999)	*With population size*: *250 elements*
	For 10 generations: [Position error: 40 mm and orientation error: 0.5°].
	For 5 generations: [Position error: 50 mm and orientation error: 1°].
Neto et al. (2019)	Average error with: [400 particles: 0.0238, 800 particles: 0.0214, 1200 particles: 0.0223 and 1600 particles: 0.0221].
Wang et al. (2012)	Average position and attitude error: x-axis: 23.3 mm and y-axis: 9.5 mm.
Burbridge et al. (2008)	RMSE < 10 mm with 50 features, RMSE < 12.5 mm with 360° camera field of view and
	RMSE < 600 mm with noise of 10°.
Kim and Oh (2008)	Position error: 600 mm.
Erturk et al. (2012)	Overall error bound of omnidirectional VSLAM: 81.1 mm [x-axis] and 74.3 mm [y-axis].
Rituerto et al. (2010)	*Error analysis using omnidirectional camera:*
	Mean of orientation error in different trajectories (Tn):
	T1: 2.29°, T2: 6.87°, T3: 6.30°, T4: 4.01° and T5: 16.61°.
	Mean of absolute estimation error of the vehicle in z coordinate in different trajectories (in mm):
	T1: 180, T2: 260, T3: 180, T4: 110 and T5: 100.
Schymura and Kolossa (2018)	*Reverberation times T_{60} of 0 s, 0.5 s and 1 s*:
	Localization fine-error: [in 0 s: 470 mm, 0.5 s: 490 mm and 1 s: 470 mm].
	Translational pose error: [in 0 s: 310 mm, 0.5 s: 320 mm and 1 s: 320 mm].
	Rotational pose errors: [in 0 s: 1.01°, 0.5 s: 1.02° and 1 s: 1.03°].
Yuen and MacDonald (2003)	Absolute position error < 500 m.
Song et al. (2018)	Average position error: x-axis: 60.25 mm and y-axis: 13.16 mm.
	Average orientation error: 0.201°.
Chang et al. (2016)	RMSE of pose estimation: x-axis: 3785 mm and y-axis: 4221.3 mm.
Low et al. (2010)	Robot localization error < 50 mm.
Ankışhan et al. (2013)	MSE: 2824.6 mm and heading angle: 3.82°.

spent on position and direction estimation (Lee et al., 2007). Hence, the localization error contains both position error and orientation error (Zhang et al., 2018). Table 10 addresses the estimated error details along with localization strategy in proposed articles.

A robot needs to access prior navigational information (relative and absolute measurements) for locating itself. The robot acquires this information while navigating in the environment. The relative information provides information regarding the robot's relative displacement. This displacement does not depend on the environment features. The relative measurement has the advantage of high frequency and low cost. However, in relative measurement, slippage and drift of the robot causes the localization error to grow unbounded over time. Therefore, in absolute measurement, the robot extracts absolute information of its position by observations made from the environment. This information does not depend on earlier position estimates. However, this measurement scheme has lower frequency, lower accuracy and higher computational costs in comparison to relative scheme.

Analysing different localization strategies, we observed that, the absolute measurements are independent of previous position estimates. This scheme does not suffer from errors growing unbounded. The absolute measurements can be used alone. However, the disadvantages recommend to combine absolute and relative position measurements for obtaining better result. The relative measurements provide accurate location information. However, at certain situations absolute measurements are utilized for correcting error caused by relative measurements. Basically, combining the information provided by different sensors, provides a best estimate of the robot's position. This is commonly known as the Multi-sensor fusion approach. A comparative study on different localization approaches suggest that in indoor environment the RFID based system is well suited due to its precise path estimation and low positioning error. However, in open space the probabilistic based localization approach is found to be quite effective. In addition to that, SLAM is a powerful approach and is more promising in unknown environments. Further the application of different evolutionary and soft computing techniques results in precise location estimation makes the localization system robust.

5. Conclusions and future direction

This paper discusses on localization strategies adopted by various authors for positioning mobile robots. We analyzed on probabilistic map-based localization and automated map building strategies along with RFID localization schemes developed for mobile robot localization. The SLAM model is an effective and acceptable localization technique for mobile robots employed in unfamiliar zones. Combining probabilistic localization approach such as EKF with SLAM increases localization and orientation accuracy, which in turn reduces the positioning error. Further, in low noise environment, EKF method is well suited to provide precise solution with higher convergence rate. In limited environment space such as indoor environments, the RFID scheme is proved to be very efficient in tracking robots. In addition to RFID, the use of evolutionary techniques, helps the robot in estimating nearly optimal path which makes these systems more robust. We observed that, the combination of RFID scheme and SLAM approach may produce better localization accuracy, more specifically in indoor environments.

During our study we also found research done on localizing brain-controlled mobile robots. These research focuses on applying map-oriented and SLAM-based localization strategies to locate brain-controlled mobile robots. These robots are controlled by the electroencephalogram (EEG) signal. Based on operational modes, these robots are categorized as direct controlled by BCI (brain-computer interface) and shared controlled BCI. In direct controlled BCI robots, BCI generates commands to control the robot directly. However, in shared controlled approach, a user (using a BCI) and an intelligent based autonomous navigation system share the control over the robots (Bi et al., 2013). In both of these categories, the robot must know its present location, and suitable path planning and navigation strategies should be incorporated to make the system more effective. As per our view, future potential direction is developing SLAM based RFID system for positioning brain-controlled mobile robots to be applicable in indoor environment and applying evolutionary techniques on SLAM based localization schemes to reduce localization error and guide the robot in planning optimal collision-free trajectory. Apart from SLAM efficient continuous localization and component mapping schemes like ARIEL and feature based extraction (Murphy, 2011) may also be combined with mobile robot localization techniques. Research on optimal orientation of EEG-based robotic systems has many considerable activities. Advance effort and success of this research would guide in developing robotic systems that may adopt effective trajectory planning scheme for efficient path planning and navigation of autonomous or semi-autonomous brain-controlled mobile robots.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Ahmad, H., Namerikawa, T., 2013. Extended Kalman filter-based mobile robot localization with intermittent measurements. Syst. Sci. Control Eng. 1 (1), 113–126. https://doi.org/10.1080/21642583.2013.864249.

Amri, M., Becis, Y., Aubry, D., Ramdani, N., 2015. May). Indoor human/robot localization using robust multi-modal data fusion. In: 2015 IEEE International Conference on Robotics and Automation (ICRA), pp. 3456–3463. https://doi.org/10.1109/ICRA.2015.7139677.

Andrade-Cetto, J., Vidal-Calleja, T., Sanfeliu, A., 2005. Unscented transformation of vehicle states in SLAM. In: Proceedings of the 2005 IEEE International Conference on Robotics and Automation, Barcelona, Spain, pp. 323–328. https://doi.org/10.1109/ROBOT.2005.1570139.

Ankışhan, H., Tartan, E.Ö., Arı, F., 2013. Square root unscented based FastSlam optimized by particle swarm optimization passive congregation. In: 2013 IEEE International Conference on Mechatronics and Automation, pp. 469–475. https://doi.org/10.1109/ICMA.2013.6617963.

Armingol, J.M., Moreno, L.E., de la Escalera, A., Salichs, M.A., 1999. A genetic algorithm for mobile robot localization using ultrasonic sensors. IFAC Proc. 32 (2), 8416–8421. https://doi.org/10.1016/S1474-6670(17)57435-2.

Ashokaraj, I.A.R., Silson, P.M.G., Tsourdos, A., White, B.A., 2009. Robust sensor-based navigation for mobile robots. IEEE Trans. Instrum. Meas. 58 (3), 551–556. https://doi.org/10.1109/TIM.2008.2005266.

Bahl, P., Padmanabhan, V.N., Balachandran, A., 2000. Enhancements to the radar user location and tracking system. Microsoft Research, 1–13.

Ball, D., Heath, S., Wiles, J., Wyeth, G., Corke, P., Milford, M., 2013. OpenRatSLAM: an open source brain-based SLAM system. Auton. Robots. 34 (3), 149–176. https://doi.org/10.1007/s10514-012-9317-9.

Bi, L., Fan, X.-A., Liu, Y., 2013. EEG-based brain-controlled mobile robots: a survey. IEEE Trans. Hum.-Mach. Syst. 43 (2), 161–176. https://doi.org/10.1109/TSMCC.2012.2219046.

Burbridge, C., Spacek, L., Condell, J., Nehmzow, U., 2008. Monocular omnidirectional vision based robot localisation and mapping. In: Proceedings of Towards Autonomous Robotic Systems, pp. 135–141.

Burgard, W., Fox, D., Hennig, D., Schmidt, T., 1996. Estimating the absolute position of a mobile robot using position probability grids. In: Proceedings of the thirteenth national conference on Artificial intelligence (AAAI'96). AAAI Press, pp. 896–901.

Caruso, D., Engel, J., Cremers, D., 2015. Large-scale direct SLAM for omnidirectional cameras. In: 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 141–148. https://doi.org/10.1109/IROS.2015.7353366.

Chang, H., Yang, W., Zhang, H., Yang, X., Chen, C., 2016. An improved FastSLAM using resmapling based on particle swarm optimization. In: 2016 IEEE 11th Conference on Industrial Electronics and Applications (ICIEA), pp. 229–234. https://doi.org/10.1109/ICIEA.2016.7603584.

Cheein, F.A.A., Cruz, C. De La, Bastos, T.F., Carelli, R., 2009. SLAM-based cross-a-door solution approach for a robotic wheelchair. Int. J. Adv. Rob. Syst. 6 (3), 20. https://doi.org/10.5772/7230.

Cheein, F.A.A., Toibero, J.M., Sciascio, F.di., Carelli, R., Pereira, F.L., 2010. Monte Carlo uncertainty maps-based for mobile robot autonomous SLAM navigation. In: 2010 IEEE International Conference on Industrial Technology, Vina del Mar, pp. 1433–1438. https://doi.org/10.1109/ICIT.2010.5472495.

Chen, L., Hu, H., McDonald-Maier, K., 2012. EKF based mobile robot localization. In: Third International Conference on Emerging Security Technologies, pp. 149–154. https://doi.org/10.1109/EST.2012.19.

Choi, J., Choi, M., Chung, W.K., 2012a. Topological localization with kidnap recovery using sonar grid map matching in a home environment. Rob. Comput. Integr. Manuf. 28 (3), 366–374. https://doi.org/10.1016/j.rcim.2011.10.008.

Choi, W., Kang, J., Oh, S., 2009. Measurement noise estimator assisted extended Kalman Filter for SLAM problem. In: 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems, St. Louis, MO, pp. 2077–2082. https://doi.org/10.1109/IROS.2009.5354525.

Choi, B., Lee, J., 2009. Mobile robot localization scheme based on RFID and sonar fusion system. In: 2009 IEEE International Symposium on Industrial Electronics, Seoul, pp. 1035–1040. https://doi.org/10.1109/ISIE.2009.5221628.

Choi, B.-S., Lee, J.-W., Lee, J.-J., Park, K.-T., 2011. A hierarchical algorithm for indoor mobile robot localization using RFID sensor fusion. IEEE Trans. Ind. Electron. 58 (6), 2226–2235. https://doi.org/10.1109/TIE.2011.2109330.

Choi, J.S., Son, B.R., Kang, H.K., Lee, D.H., 2012b. Indoor localization of Unmanned Aerial Vehicle based on passive UHF RFID systems. In: 2012 9th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI), Daejeon, pp. 188–189. https://doi.org/10.1109/URAI.2012.6462966.

Civera, J., Davison, A.J., Montiel, J.M.M., 2008. Inverse depth parametrization for monocular SLAM. IEEE Trans. Rob. 24 (5), 932–945. https://doi.org/10.1109/TRO.2008.2003276.

D'Alfonso, L., Griffo, A., Muraca, P., Pugliese, P., 2013. A SLAM algorithm for indoor mobile robot localization using an Extended Kalman filter and a segment based environment mapping. In: 2013 16th International Conference on Advanced Robotics (ICAR), pp. 1–6. https://doi.org/10.1109/ICAR.2013.6766461.

Dastjerdi, H.V., Menhaj, M.B., Shataei, S., 2016. Self-localization of humanoid robots using particle swarm optimization algorithm. In: 2016 Artificial Intelligence and Robotics (IRANOPEN), Qazvin, pp. 98–102. https://doi.org/10.1109/RIOS.2016.7529497.

Davison, A.J., Reid, I.D., Molton, N.D., Stasse, O., 2007. MonoSLAM: real-time single camera SLAM. IEEE Trans. Pattern Anal. Mach. Intell. 29 (6), 1052–1067. https://doi.org/10.1109/TPAMI.2007.1049.

Dellaert, F., Burgard, W., Fox, D., Thrun, S., 1999a. Using the CONDENSATION algorithm for robust, vision-based mobile robot localization. In: Proceedings. 1999 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (Cat. No PR00149), Fort Collins, CO, USA, pp. 588–594. https://doi.org/10.1109/CVPR.1999.784976.

Dellaert, F., Fox, D., Burgard, W., Thrun, S., 1999b. Monte Carlo localization for mobile robots. In: Proceedings 1999 IEEE International Conference on Robotics and Automation (Cat. No.99CH36288C), Detroit, MI, USA, pp. 1322–1328. https://doi.org/10.1109/ROBOT.1999.772544.

DiGiampaolo, E., Martinelli, F., 2018. A robotic system for localization of passive UHF-RFID tagged objects on shelves. IEEE Sens. J. 18 (20), 8558–8568. https://doi.org/10.1109/JSEN.2018.2865339.

Ekkahau Inc., 2019. <https://www.ekahau.com/> (accessed 13 August 2019).

Erturk, H., Tuna, G., Mumcu, T.V., Gulez, K., 2012. A performance analysis of omnidirectional vision based simultaneous localization and mapping 7389. In: Huang, D.S., Jiang, C., Bevilacqua, V., Figueroa, J.C. (Eds.), Intelligent Computing Technology. ICIC 2012, Lecture Notes in Computer Science. Springer, Berlin, Heidelberg, pp. 407–414. https://doi.org/10.1007/978-3-642-31588-6_53.

Esteves, J.S., Carvalho, A., Couto, C., 2006. Position and orientation errors in mobile robot absolute self-localization using an improved version of the generalized geometric triangulation algorithm. In: 2006 IEEE International Conference on Industrial Technology, Mumbai, pp. 830–835. https://doi.org/10.1109/ICIT.2006.372345.

Fernández, L., Payá, L., Reinoso, O., Jimenez, L.M., 2014. Appearance-based approach to hybrid metric-topological simultaneous localisation and mapping. IET Intel. Transport Syst. 8 (8), 688–699. https://doi.org/10.1049/itr2.v8.810.1049/iet-its.2013.0086.

Georgiev, A., Allen, P.K., 2004. Localization methods for a mobile robot in urban environments. IEEE Trans. Rob. 20 (5), 851–864. https://doi.org/10.1109/TRO.2004.829506.

Gutmann, J.-S., Schlegel, C., 1996. AMOS: comparison of scan matching approaches for self-localization in indoor environments. In: Proceedings of the First Euromicro Workshop on Advanced Mobile Robots (EUROBOT '96), Kaiserslautern, Germany, pp. 61–67. https://doi.org/10.1109/EURBOT.1996.551882.

Hahnel, D., Burgard, W., Fox, D., Fishkin, K., Philipose, M., 2004. Mapping and localization with RFID technology. In: IEEE International Conference on Robotics and Automation, 2004. Proceedings. ICRA '04. 1(2004), New Orleans, LA, USA, pp. 1015–1020. https://doi.org/10.1109/ROBOT.2004.1307283.

Havangi, R., 2019. Mobile robot localization based on PSO estimator. Asian J. Control, Wiley 21 (4), 2167–2178. https://doi.org/10.1002/asjc.v21.410.1002/asjc.2004.

Havangi, R., Nekoui, M.A., Teshnehlab, M., 2010. A multi swarm particle filter for mobile robot localization. Int. J. Comput. Sci. 7, 15–22.

Havangi, R., Taghirad, H.D., Nekoui, M.A., Teshnehlab, M., 2014. A square root unscented FastSLAM with improved proposal distribution and resampling. IEEE Trans. Ind. Electron. 61 (5), 2334–2345. https://doi.org/10.1109/TIE.2013.2270211.

Hsu, Y.-F., Huang, C.-H., Huang, W.-R., Chu, W.-C., 2013. An improved minimum-cost pathfinding algorithm for mobile robot navigation. J. Adv. Comput. Networks 1, 189–193. https://doi.org/10.7763/JACN.2013.V1.38.

Huo, J., Ma, L., Yu, Y., Wang, J., 2013. July). Hybrid algorithm based mobile robot localization using DE and PSO. In: Proceedings of the 32nd Chinese Control Conference, pp. 5955–5959.

Hwang, C., Chen, T., Hung, J.Y., 2017. Neural-network-based mobile RFID localization system. In: IECON 2017 - 43rd Annual Conference of the IEEE Industrial Electronics Society, Beijing, pp. 6051–6056. https://doi.org/10.1109/IECON.2017.8217050.

Jajulwar, K., Deshmukh, A., 2015. Design of mobile robot navigation system using SLAM and adaptive tracking controller with particle swarm optimization for indoor environment monitoring. IOSR J. Comput. Eng. 17, 59–63.

Janah, M., Fujimoto, Y., 2018. Study comparison between firefly algorithm and particle swarm optimization for SLAM problems. In: 2018 International Power Electronics Conference (IPEC-Niigata 2018 -ECCE Asia), Niigata, pp. 681–687. https://doi.org/10.23919/IPEC.2018.8507877.

Javad, Z., Cai, Y., Majid, Y., 2017. Comparing EKF and SPKF algorithms for simultaneous localization and mapping (SLAM). J. Robot., Network. Artif. Life 3, 217–220.

Kim, S., Oh, S.-Y., 2008. SLAM in indoor environments using omni-directional vertical and horizontal line features. J. Intell. Robot Syst. 51 (1), 31–43. https://doi.org/10.1007/s10846-007-9179-0.

Klaess, J., Stueckler, J., Behnke, S., 2012. Efficient Mobile Robot Navigation using 3D Surfel Grid Maps. In: ROBOTIK, 7th German Conference on Robotics, pp. 1–4.

Krumm, J., Harris, S., Meyers, B., Brumitt, B., Hale, M., Shafer, S., 2000. Multi-camera multi-person tracking for EasyLiving. In: Proceedings Third IEEE International Workshop on Visual Surveillance, pp. 3–10. https://doi.org/10.1109/VS.2000.856852.

Lee, Hyun-Jeong, Kim, M.S., Lee, M.C., 2007. Technique to correct the localization error of the mobile robot positioning system using an RFID. In: SICE Annual Conference 2007, Takamatsu, pp. 1506–1511. https://doi.org/10.1109/SICE.2007.4421221.

Leonard, J.J., Durrant-Whyte, H.F., 1992. In: Directed Sonar Sensing for Mobile Robot Navigation. Springer Science+Business Media, LLC, United Kingdom. https://doi.org/10.1007/978-1-4615-3652-9.

Li, J., Liu, Y., Yuan, W., Li, Z., 2018. Improved SLAM and Motor Imagery Based Navigation Control of a Mobile Robot. In: 2018 3rd International Conference on Advanced Robotics and Mechatronics (ICARM), pp. 36–41. https://doi.org/10.1109/ICARM.2018.8610763.

Liu, Y., Li, J., Li, Z., 2018. An indoor navigation control strategy for a brain-actuated mobile robot. In: 2018 3rd International Conference on Advanced Robotics and Mechatronics (ICARM), pp. 13–18. https://doi.org/10.1109/ICARM.2018.8610705.

Low, W., Nagarajan, R., Yaacob, S., 2010. Visual based SLAM using modified PSO. In: 2010 6th International Colloquium on Signal Processing & its Applications, Mallaca City, pp. 1–5. https://doi.org/10.1109/CSPA.2010.5545267.

Mali, S., 2015. Mobile robot localization using multi-objective optimization. Int. J. Latest Technol. Eng., Manag. Appl. Sci. -IJLTEMAS 4, 21–25.

Martinelli, F., 2015. A robot localization system combining RSSI and phase shift in UHF-RFID signals. IEEE Trans. Control Syst. Technol. 23 (5), 1782–1796. https://doi.org/10.1109/TCST.2014.2386777.

Martinez-Cantin, R., Castellanos, J.A., 2005. Unscented SLAM for large-scale outdoor environments. In: 2005 IEEE/RSJ International Conference on Intelligent Robots and Systems, Edmonton, Alta, pp. 3427–3432. https://doi.org/10.1109/IROS.2005.1545002.

Matsuo, K., Miura, J., 2012. October). Outdoor visual localization with a hand-drawn line drawing map using FastSLAM with PSO-based mapping. In: 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 202–207. https://doi.org/10.1109/IROS.2012.6385506.

Mi, J., Takahashi, Y., 2015a. Performance analysis of mobile robot self-localization based on different configurations of RFID system. In: 2015 IEEE International Conference on Advanced Intelligent Mechatronics (AIM), Busan, pp. 1591–1596. https://doi.org/10.1109/AIM.2015.7222770.

Mi, J., Takahashi, Y., 2015b. Low cost design of HF-band RFID system for mobile robot self-localization based on multiple readers and tags. In: 2015 IEEE International Conference on Robotics and Biomimetics (ROBIO), pp. 194–199. https://doi.org/10.1109/ROBIO.2015.7418766.

Milford, M., Wyeth, G., 2010. Persistent navigation and mapping using a biologically inspired SLAM system. Int. J. Robot. Res. 29 (9), 1131–1153. https://doi.org/10.1177/0278364909340592.

Mohamed, A.Z., Lee, S.H., Hsu, H.Y., 2011. Autonomous mobile robot system concept based On PSO path planner and vSLAM. In: 2011 IEEE International Conference on Computer Science and Automation Engineering, Shanghai, pp. 92–97. https://doi.org/10.1109/CSAE.2011.5952810.

Motroni, A., Nepa, P., Tripicchio, P., Unetti, M., 2018a. SAR-based indoor localization of UHF-RFID tags via mobile robot. In: 2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Nantes, pp. 1–8.

Motroni, A., Nepa, P., Tripicchio, P., Unetti, M., 2018b. A multi-antenna SAR-based method for UHF RFID Tag Localization via UGV. In: 2018 IEEE International Conference on RFID Technology & Application (RFID-TA), Macau, pp. 1–6. https://doi.org/10.1109/RFID-TA.2018.8552780.

Müller, S., Weber, C., Wermter, S., 2014. RatSLAM on humanoids - a bio-inspired slam model adapted to a humanoid robot. In: Wermter, S. (Ed.), Artificial Neural Networks and Machine Learning – ICANN 2014, ICANN 2014, Lecture Notes in Computer Science. Springer, Cham, pp. 789–796. https://doi.org/10.1007/978-3-319-11179-7_99.

Murphy, R.R., 2011. Introduction to AI Robotics. PHI Learning Private Limited, New Delhi.

Negenborn, R., 2003. Robot Localization and Kalman Filters: On finding your position in a noisy world Master of Science. Thesis. Utrecht University.

Neto, A.A., Macharet, D.G., Campos, V.C.da.S., Campos, M.F.M., 2009. Adaptive complementary filtering algorithm for mobile robot localization. J. Braz. Comput. Soc. 15, 19–31. https://doi.org/10.1007/BF03194503.

Neto, W.A., Pinto, M.F., Marcato Jr., A.L.M., da Silva, I.C., Fernandes, D. de A., 2019. Mobile robot localization based on the novel leader-based bat algorithm. J. Control, Autom. Electr. Syst. 30, 337–346. https://doi.org/10.1007/s40313-019-00453-2.

Panigrahi, P.K., Tripathy, H.K., 2015a. Analysis on intelligent based navigation and path finding of autonomous mobile robot. In: Mandal, J., Satapathy, S., Sanyal, M.K., Sarkar, P., Mukhopadhyay, A. (Eds.), Information Systems Design and Intelligent Applications, Advances in Intelligent Systems and Computing. Springer, New Delhi, pp. 219–232. https://doi.org/10.1007/978-81-322-2250-7_22.

Panigrahi, P.K., Tripathy, H.K., 2015b. Low complexicity graph based navigation and path finding of mobile robot using BFS. In: Proceedings of the 2nd International Conference on Perception and Machine Intelligence (PerMIn '15). ACM, New York, NY, USA, pp. 189–195. https://doi.org/10.1145/2708463.2709068.

Park, S., Hashimoto, S., 2009a. Indoor localization for autonomous mobile robot based on passive RFID. In: 2008 IEEE International Conference on Robotics and Biomimetics, Bangkok, pp. 1856–1861. https://doi.org/10.1109/ROBIO.2009.4913284.

Park, S., Hashimoto, S., 2009b. Autonomous mobile robot navigation using passive RFID in indoor environment. IEEE Trans. Ind. Electron. 56 (7), 2366–2373. https://doi.org/10.1109/TIE.2009.2013690.

Pinto, A.M., Moreira, António.P., Costa, P.G., 2015. A localization method based on map-matching and particle swarm optimization. J Intell Robot Syst 77 (2), 313–326. https://doi.org/10.1007/s10846-013-0009-2.

Pöpperl, M., Dobrev, Y., Gottinger, M., Mandel, C., Jakoby, R., Vossiek, M., 2016. Chipless UWB TDR RFID landmark-based positioning using polarimetric filtering. In: 2016 IEEE MTT-S International Conference on Microwaves for Intelligent Mobility (ICMIM), San Diego, CA, pp. 1–4. https://doi.org/10.1109/ICMIM.2016.7533924.

Ubisense Products, 2019. <https://www.ubisense.net/> (accessed 13 August 2019).

Rajurkar, S.D., Kar, A.K., Goswami, S., Verma, N.K., 2016. Optimal path estimation and tracking for an automated vehicle using GA optimized fuzzy controller. In: 2016 11th International Conference on Industrial and Information Systems (ICIIS), Roorkee, pp. 365–370. https://doi.org/10.1109/ICIINFS.2016.8262967.

Rampinelli, M., Covre, V., de Queiroz, F., Vassallo, R., Bastos-Filho, T., Mazo, M., 2014. An intelligent space for mobile robot localization using a multi-camera system. Sensors 14 (8), 15039–15064. https://doi.org/10.3390/s140815039.

Rituerto, A., Puig, L., Guerrero, J.J., 2010. Comparison of omnidirectional and conventional monocular systems for visual slam. In: 10th Workshop on Omnidirectional Vision, Camera Networks and Non-classical Cameras (OMNIVIS) co-located with Robotics: Science & Systems (RSS), pp. 1–13.

Schiele, B., Crowley, J.L., 1994. A comparison of position estimation techniques using occupancy grids. In: Proceedings of the 1994 IEEE International Conference on Robotics and Automation, San Diego, CA, USA, pp. 1628–1634. https://doi.org/10.1109/ROBOT.1994.351357.

Schymura, C., Kolossa, D., 2018. Potential-field-based active exploration for acoustic simultaneous localization and mapping. In: 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). https://doi.org/10.1109/ICASSP.2018.8461655.

Shirehjini, A.A.N., Yassine, A., Shirmohammadi, S., 2012. An RFID-based position and orientation measurement system for mobile objects in intelligent environments. IEEE Trans. Instrum. Meas. 61 (6), 1664–1675. https://doi.org/10.1109/TIM.2011.2181912.

Siegwart, R., Nourbakhsh, I.R., Scaramuzza, D., 2011. Introduction to Autonomous Mobile Robots. PHI Learning Private Limited, New Delhi.

Simmons, R., Koenig, S., 1995. Probabilistic robot navigation in partially observable environments. In: Proceedings of the 14th international joint conference on Artificial intelligence (IJCAI'95). Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, pp. 1080–1087.

Somlyai, L., Vámossy, Z., 2015. SLAM algorithm for mobile robot localization with RGB-D camera. In: Fluids, Heat and Mass Transfer, Mechanical and Civil Engineering, pp. 89–94.

Song, K.-T., Chiu, Y.-H., Kang, L.-R., Song, S.-H., Yang, C.-A., Lu, P.-C., Ou, S.-Q., 2018. Navigation control design of a mobile robot by integrating obstacle avoidance and LiDAR SLAM. In: 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Miyazaki, Japan, pp. 1833–1838. https://doi.org/10.1109/SMC.2018.00317.

Sudantha, B.H., Sumathipala, K.A.S.N., Premachandra, C., Warnakulasooriya, K.M.H. K., Elvitigala, C.S., Jayasuriya, Y.P., 2017. Adaptive navigation and motion planning for a mobile track robot. In: 2017 Joint 17th World Congress of International Fuzzy Systems Association and 9th International Conference on Soft Computing and Intelligent Systems (IFSA-SCIS), Otsu, pp. 1–5. https://doi.org/10.1109/IFSA-SCIS.2017.8023304.

Suliman, C., Cruceru, C., Moldoveanu, F., 2010. Mobile robot position estimation using the Kalman filter. Sci. Bull. Petru Maior Univ. Tirgu Mures Inter-Eng. 6 (XXIII), 75–78.

Vahdat, A.R., NourAshrafoddin, N., Ghidary, S.S., 2007. Mobile robot global localization using differential evolution and particle swarm optimization. In: 2007 IEEE Congress on Evolutionary Computation, Singapore, pp. 1527–1534. https://doi.org/10.1109/CEC.2007.4424654.

Valiente, D., Gil, A., Fernández, L., Reinoso, Óscar, 2014. A comparison of EKF and SGD applied to a view-based SLAM approach with omnidirectional images. Rob. Auton. Syst. 62 (2), 108–119. https://doi.org/10.1016/j.robot.2013.11.009.

Vasiljević, G., Miklić, D., Draganjac, I., Kovačić, Z., Lista, P., 2016. High-accuracy vehicle localization for autonomous warehousing. Rob. Comput. Integr. Manuf. 42, 1–16. https://doi.org/10.1016/j.rcim.2016.05.001.

Wang, H., Liu, W., Zhang, F., Yang, S.X., Zhang, L., 2015. A GA-fuzzy logic based extended Kalman filter for mobile robot localization. In: 2015 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD), Zhangjiajie, pp. 319–323. https://doi.org/10.1109/FSKD.2015.7381961.

Wang, J., Takahashi, Y., 2016. Particle filter based landmark mapping for SLAM of mobile robot based on RFID system. In: 2016 IEEE International Conference on Advanced Intelligent Mechatronics (AIM), pp. 870–875. https://doi.org/10.1109/AIM.2016.7576878.

Wang, K., Xia, G., Zhu, Q., Yu, Y., Wu, Y., Wang, Y., 2012. June). The SLAM algorithm of mobile robot with omnidirectional vision based on EKF. In: 2012 IEEE International Conference on Information and Automation, pp. 13–18. https://doi.org/10.1109/ICInfA.2012.6246774.

Want, R., Hopper, A., Falcão, V., Gibbons, J., 1992. The active badge location system. ACM Trans. Inf. Syst. 10 (1), 91–102. https://doi.org/10.1145/128756.128759.

Wu, H., Tao, B., Gong, Z., Yin, Z., Ding, H., 2019. A fast UHF RFID localization method using unwrapped phase-position model. IEEE Trans. Autom. Sci. Eng. 16, 1698–1707. https://doi.org/10.1109/TASE.2019.2895104.

Xue, Y., 2016. Intelligent object localization system based on activity theory in home environment. In: 12th World Congress on Intelligent Control and Automation (WCICA), pp. 3071–3076. https://doi.org/10.1109/WCICA.2016.7578254.

Yamada, T., Nakamura, S., Shikano, K., 1996. Robust speech recognition with speaker localization by a microphone array. In: Proceeding of Fourth International Conference on Spoken Language Processing ICSLP '96, Philadelphia, PA, USA, pp. 1317–1320. https://doi.org/10.1109/ICSLP.1996.607855.

Yan, W., Weber, C., Wermter, S., 2011. A hybrid probabilistic neural model for person tracking based on a ceiling-mounted camera. J. Ambient Intell. Smart Environ. 3, 237–252. https://doi.org/10.3233/AIS-2011-0111.

Yang, Q., Taylor, D.G., Durgin, G.D., 2018. April). Kalman filter based localization and tracking estimation for HIMR RFID systems. In: 2018 IEEE International Conference on RFID (RFID), Orlando, FL, pp. 1–5. https://doi.org/10.1109/RFID.2018.8376199.

Yuan, Y., Li, Z., Liu, Y., 2018. Brain teleoperation of a mobile robot using deep learning technique. In: 2018 3rd International Conference on Advanced Robotics and Mechatronics (ICARM), pp. 54–59. https://doi.org/10.1109/ICARM.2018.8610711.

Yuan, Y., Su, W., Li, Z., Shi, G., 2019. Brain-computer interface-based stochastic navigation and control of a semiautonomous mobile robot in indoor environments. IEEE Trans. Cogn. Dev. Syst. 11 (1), 129–141. https://doi.org/10.1109/TCDS10.1109/TCDS.2018.2885774.

Yuen, D.C.K., MacDonald, B.A., 2003. An evaluation of the sequential Monte Carlo technique for simultaneous localisation and map-building. In: 2003 IEEE International Conference on Robotics and Automation (Cat. No.03CH37422), Taipei, Taiwan, pp. 1564–1569. https://doi.org/10.1109/ROBOT.2003.1241817.

Zhang, J., Lyu, Y., Patton, J., Periaswamy, S.C.G., Roppel, T., 2018. BFVP: A probabilistic UHF RFID tag localization algorithm using Bayesian filter and a variable power RFID Model. IEEE Trans. Ind. Electron. 65 (10), 8250–8259. https://doi.org/10.1109/TIE.2018.2803720.

Zi, B., Lin, J., Qian, S., 2015. Localization, obstacle avoidance planning and control of a cooperative cable parallel robot for multiple mobile cranes. Rob. Comput. Integr. Manuf. 34, 105–123. https://doi.org/10.1016/j.rcim.2014.11.005.