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Empowering autonomous indoor navigation with informed machine learning techniques

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ABSTRACT

This paper proposes the application of informed machine learning technique to enhance the performance of an autonomous indoor navigation system by leveraging prior knowledge and additional data during training. The system includes simultaneous localization and mapping method for perform two prime functionalities of the localization, and mapping. By integrating machine learning, the system achieves a higher level of autonomy. It involves incorporating extra data alongside a priori knowledge gained from system training, resulting in improved efficiency and autonomy. The optimization of the proposed system model's training process utilizes the stochastic gradient descent algorithm to efficiently handle large volumes of real-time data. Through simulations, the effectiveness of the suggested informed machine learning technique is demonstrated, showcasing its superior performance in autonomous indoor navigation.

1. Introduction

Any navigation system is a computer system designed to provide details for navigation in terms of a map, suggested travel directions, location of current existence, details of traffic congestion, and so on [1]. If the system is an autonomous navigation system, it directly provides the direction to be navigated, as in a robotic examination probe, for example [2].

Unlike the outdoor navigation system, an indoor navigation system could not use Global Positioning System (GPS), as the satellite signals made use of the GPS would not pass-through walls and the ceilings present [3]. So, the Indoor Positioning System (IPS) uses the available indoor signalling technologies like Bluetooth, Wi-Fi, and short-range radio ultra-wideband communication to enable indoor navigation [4]. To incorporate the indoor navigation system in an environment, a complete map representing the detailed floor plan along with the details of the obstructions positioned within is the key credential requirement [5]. An autonomous indoor navigation system is a fully automated self-navigating system, which is trained using a machine learning algorithm provided with all possible ways of traversing directions to and from, along with the available obstruction details, within the given indoor environment shown in

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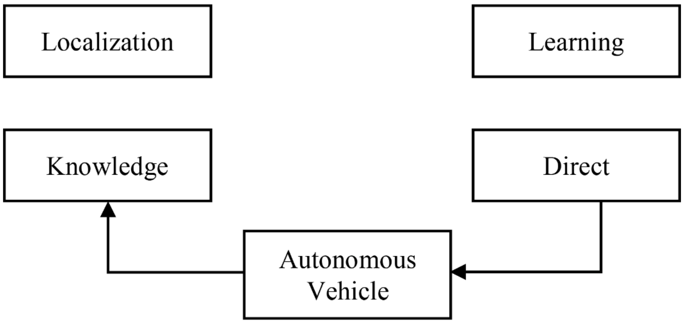

Fig. 1. Pipeline of Autonomous Navigation

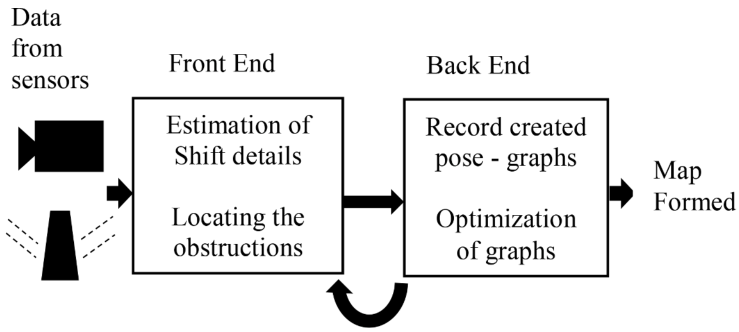

Fig. 2. SLAM -Functional Blocks

Fig. 1 [6].

Due to their affordability and high stability, mobile robots find use in applications including food service, household cleaning, and rescue operations. To fulfill these needs, these robots need to poses sensors and building maps. For, these will help them become aware of the environment and thereby determine their travel trajectories. Two of the challenges that restrict the practical applications of autonomous indoor navigation are poor map construction accuracy and suboptimal path planning.

But in case a possible solution goes missing in the training phase, and there are high chances of accidental happenings leading to mishaps, which could be avoided by providing the additional system data of information apart from the knowledge given through the phase of training the system [7]. This, in turn, makes an informed machine learning technique drive the given autonomous indoor navigation system [8].

The remaining content of the paper is organized as: In Section II, the Simultaneous Localization and Mapping procedure is comprehensively detailed. Section III elaborates on the concept of Informed Machine Learning and its significance in achieving higher system autonomy. In Section IV, the suggested system model is introduced, and the utilization of the Stochastic Gradient Descent Algorithm for optimization is explained. The simulation results demonstrating the effectiveness of the proposed technique are discussed in Section V. Finally, in Section VI, the paper concludes with comprehensive discussions, highlighting the potential of the proposed approach in advancing autonomous indoor navigation.

2. Simultaneous localization and mapping (SLAM)

SLAM [9] is typically a method involved in the design of an autonomous navigation system. As the name says, it helps the system to localize the navigation using the map built synchronously, making it a Synchronous / Simultaneous Localization and Mapping methodology. Any navigation system aims to route up the path and avoid collision with the obstructions available along the path that had already been planned.

The SLAM algorithm helps the navigation system map even unknown operation scenarios. The complete functioning of the SLAM could be briefed to be comprised of two functional blocks, namely the front-end and the back-end processing units. The front-end processing unit includes the processing block processing on the signals received from the sensors available at the indoor navigating system [10]. The back-end processing unit includes the post processing blocks and is termed sensor-agnostic concerning its functionality. The post-processing involves the optimization of the pose - graphs being involved in the complete formation of the map [11].

There are two types of SLAM methodologies available depending on the type through which the input is drawn to the front-end processing unit, namely visual SLAM, and Light Detection and Ranging SLAM [12], as shown in Fig. 2.

The visual SLAM is based on visual information captured may be from a camera or an image sensor, for that matter. The steps involved in the visual SLAM go in order. Images are captured employing camera(s) [13]. The distorted images are tried to be

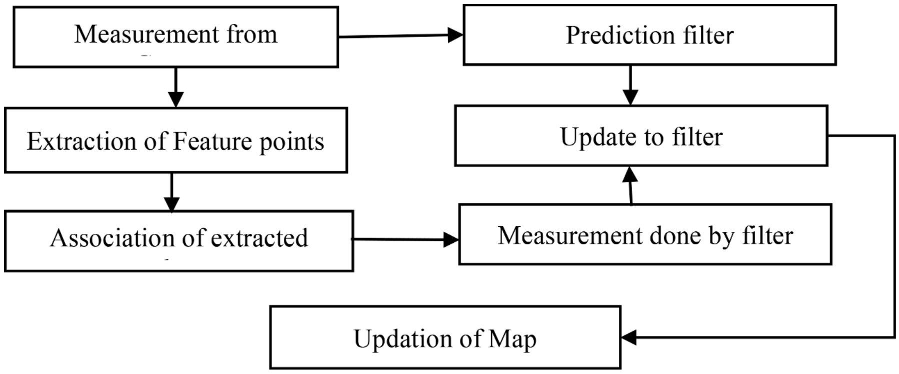

Fig. 3. Filter-based visual SLAM

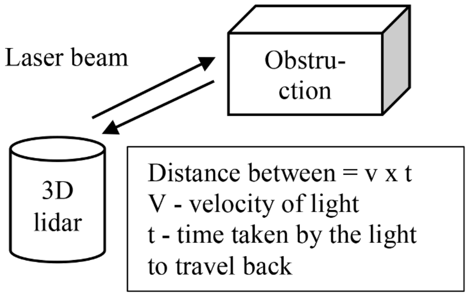

Fig. 4. Functioning of a 3D lidar

undistorted to make them close enough to the real appearance, and then the feature points are extracted. A feature point is a set of pixels that seem unique and can be identified consistently from an image. Following the feature extraction, the extracted features are mapped concerning their position estimated in space leading to data association. The next step is to keep track of the updates in the navigation's position and direction and keep updating the traverse map [14].

The visual SLAM is indeed cost-effective. The camera-captured image can provide a huge amount of information in a single picture, making it easier to plot enough points in each captured frame. In visual SLAM systems, the Enhanced Kalman Filter (EKF) concept is vital in updating the map regarding location and pose. An EKF helps provide linear values, having predicted, taking up non-linear systems, for that instance, and giving values measured at their mean [15].

It uses an approach typically probabilistic in nature, considering the previously made measurements and relating them with the newly captured pose from the camera. It uses a state vector and a covariance matrix corresponding to each feature being extracted in the process of relating. Every parameter of consideration is assumed to be Gaussian in nature. The increase in observation points makes the process complex and expensive [16].

The inevitable re-projection error in a visual SLAM should be minimized as the visual SLAM usually functions in real-time, as shown in Fig. 3. This is done using a process called bundle adjustment. The data concerning location and mapping requires bundle adjustment, and they both happen to undergo the process at the same instant to make the process happen faster before they merge [17].

The lidar SLAM is based on eye-safe LASER light. It resembles RAdio Detecting And Ranging (RADAR) communication to some extent because the lidar SLAM uses a lidar sensor that emits laser light bean to the immediate surrounding along the direction of traverse and detects the light beam being bounced back by the obstructions present, and try to calculate the distance of the location of the concerned object of obstruction concerning the lidar sensor. Unlike the 2D lidar, a 3D doesn't emit a single laser beam sweeping along a plane. Instead, it emits multiple beams of laser sweeping concerning a 3D space. The number of channels in recent days is 128, which refers to the number of beams [18].

Fig. 4 explains the complete functioning of a 3D lidar could be divided into two major blocks: the front end aiming at the tracking process and the back end aiming at the mapping process. The tracking process at the front end of the lidar starts with the received distorted form of the surroundings represented as the autonomous navigation system keeps traversing, and the lidars keep varying in their position with every sweep. So, they are deliberately required to be undistorted first. Concerning the previous position and the direction of motion, the next move of the system is predicted as accurately as possible considering the smallest positional change resulting in precise positioning of the points [19].

The next step is to find and shortlist the points required to predict the position and orientation of the autonomous system to drive it in the desired direction of travel. This involves the process called voxelization [20]. It means it is a process in which an object is segmented into smaller cube-shaped units called voxels. It is like a 2D pixel being represented in 3D cubes. Shortlisted data points are

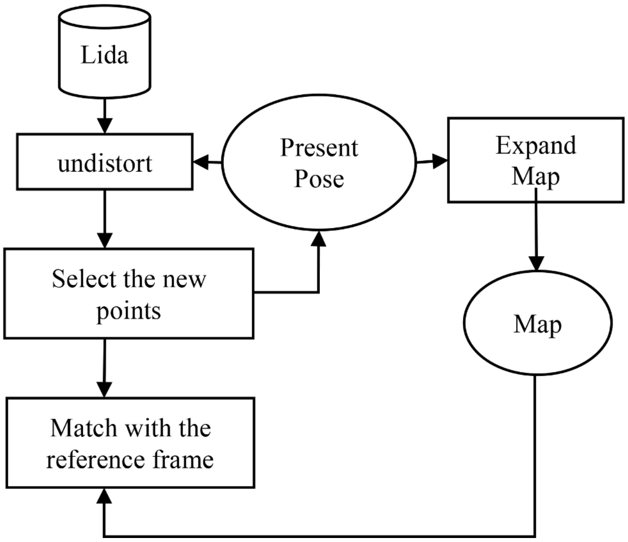

Fig. 5. Functioning of a lidar SLAM

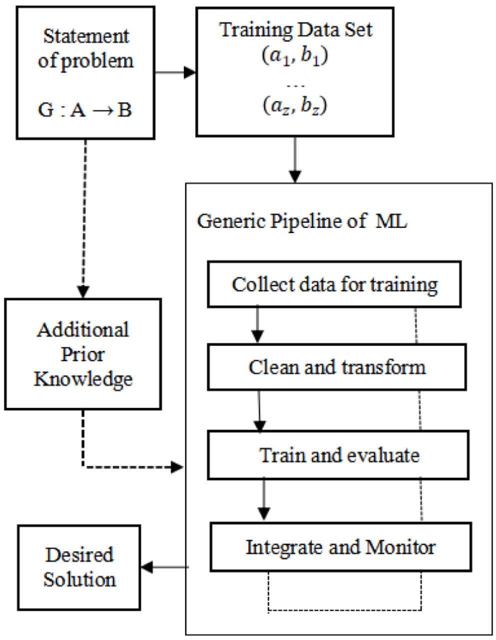

Fig. 6. Functional flow of Informed Machine Learning Algorithm.

represented as a voxel on a uniformly positioned 3D grid [21].

After the process, the points are compared with the previous or the reference frame to predict the next pose of the system. The mapping is done by adding the points determined onto the existing map with the points mapped previously, leading to the expansion of the map [22].

Fig. 5 above briefs the complete functioning of a lidar SLAM.

3. Informed machine learning algorithm

Machine learning [23] makes use of data set trying to contain all possible solutions for a given problem statement and trains the computing system with the data set in such a way that the system gets trained to arrive at the correct solutions for situations even if not given in the training data set.

In other words, machine learning helps the system gain knowledge from the training phase and react to real-time problems with

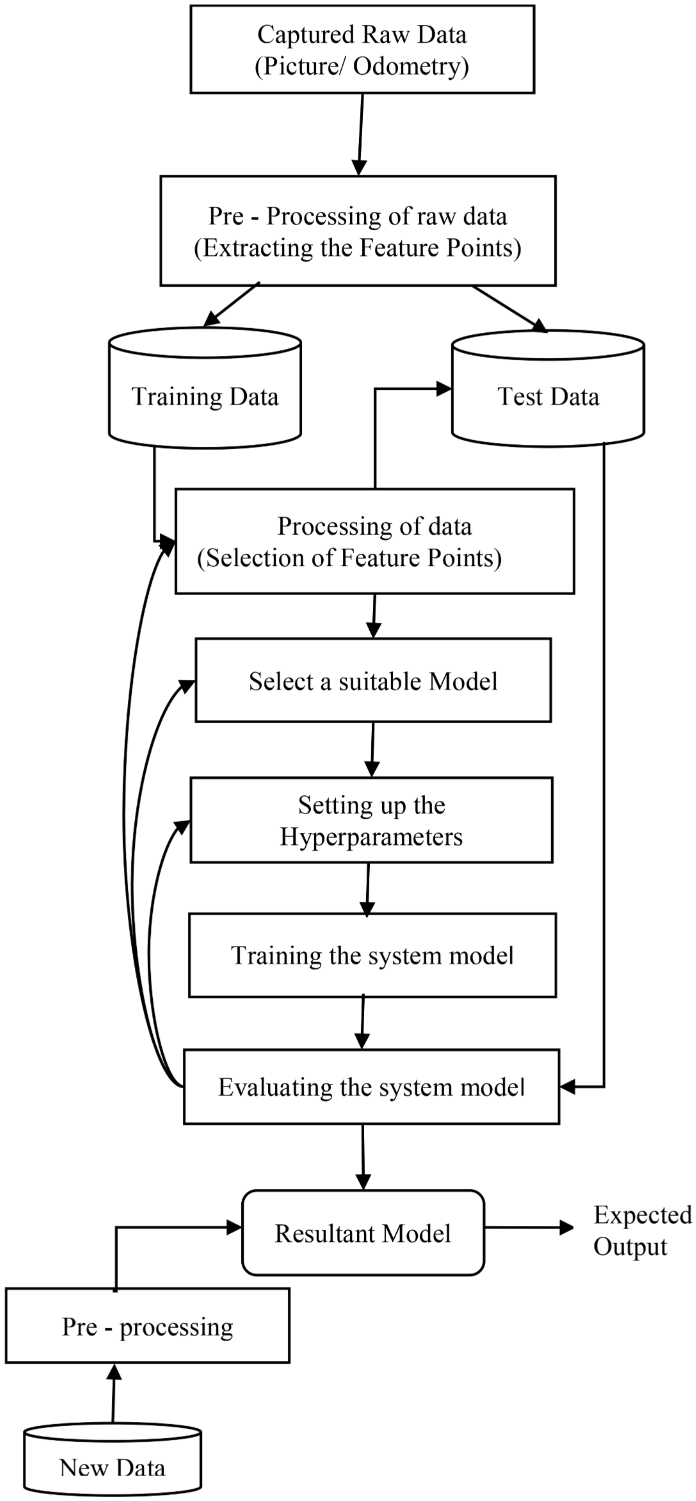

Fig. 7. Pipeline of a Machine learning algorithm for navigation.

appropriate answers, just like a human being does. One example of machine learning techniques used for autonomous indoor navigation are reinforcement learning. In this technique, the algorithm employs a trial and error method, and over time learns to make the right navigation decisions.

So, the key functioning of the autonomous system depends on how well the data set involved in the training phase was effective

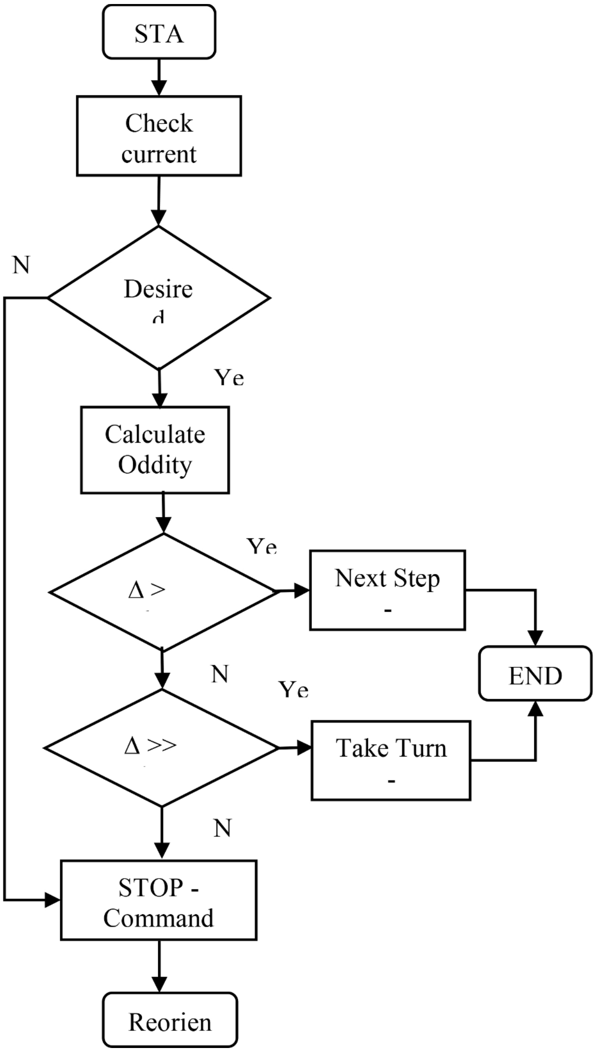

Fig. 8. Flowchart - Autonomous Indoor Navigation System

enough to include every possible condition of the input combination and the desired solutions. If there were some missing data in the training phase, though the trained system would try to learn and react to situations outside the training cases, the chances of being erroneous are higher.

So, to overcome this shortcoming, Informed machine learning has been suggested. Informed machine learning is yet another machine learning algorithm. Still, in this algorithm, it is said that the system acquiring knowledge from being trained with an effective training data set is also provided with some additional information based on the gained prior knowledge.

Fig. 6 above represents the flow of information according to the informed machine learning algorithm. The additional information would take up any form of data representation, namely, a nodal graph, algebraic or differential equation forms, logical expressions, simulation-based outputs, probability distribution functions, suggestions, and solutions from renowned experts.

The key point to be considered in this task is the nature of the source from which the additional information is drawn. Secondly, the suitable way the extracted information is being represented; Thirdly, the step in which the represented data is included in the pipeline process of learning and every consideration strictly holds good concerning the application to which the destined system is trained to be autonomous.

A good machine learning algorithm has four main goals to be achieved:

- [2] A precise and efficient data set for training.
- [2] The data set entries should be of the highest accuracy with no errors.
- [2] The model should be understandable for any human looking into it.
- [2] The system model should be capable of being adapted to the possible knowledge congruence.

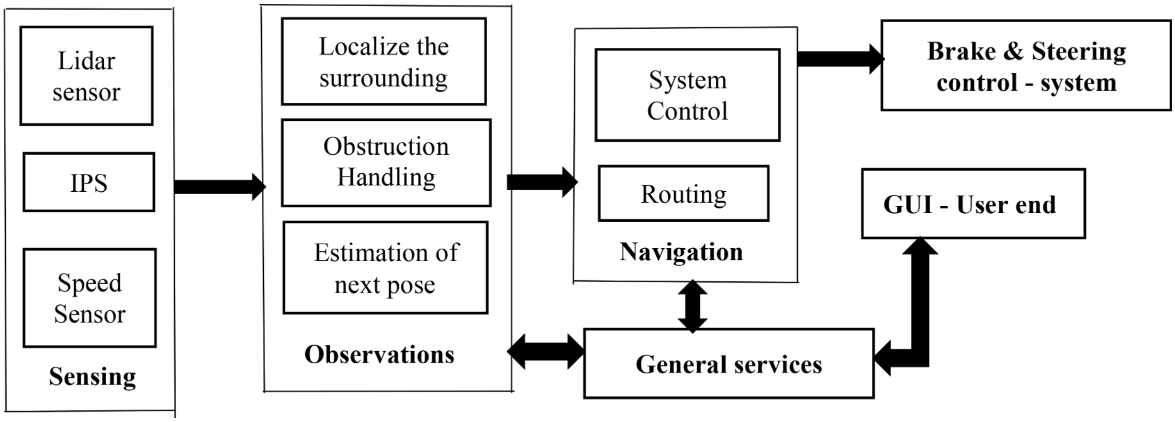

Fig. 9. A complete autonomous navigation system

So, integrating the additional information should be taken care of because any machine learning algorithm tries to train with fewer data. Integrating the additional information into the hyper-parameter list would be of better help because the information added is trustworthy and accurate and enables the system to be of good knowledge unity on its own.

If the possible representation of the given additional data takes up an equation format, then probably there are integrated into the processing pipeline via the learning algorithm flow itself. The below Fig. 7 shows the complete process of a typical machine learning algorithm pipeline flows in detail.

The design of the informed machine learning algorithm-based technique, at first, requires the complete study of the surrounding in which the system is supposed to be deployed, stating all possible to and from destined routes of a traverse along with the static obstructions present along the path and the possible dynamic obstructions that would appear on the go.

This forms the complete data set. The constructed training data set is fine-tuned for the accuracy of the data, and then the system is trained accordingly. After being trained and tested using the training data set and test data set, respectively, the system's performance is evaluated. If the system functions following the desired requirements, then the system model is fine-tuned, and the refined model is ready to deploy.

The completely trained system deployed in the autonomous navigation vehicle designed for indoors, when used, would make use of the acquired knowledge along with the captured additional real-time information to efficiently navigate the autonomous vehicle seamlessly towards the desired destination from the given point of start carefully avoiding the obstructions along the path. Hence, it becomes an informed machine-learning technique-based autonomous indoor navigation system.

About the amount of data involved, the additional information obtained in real-time adds to the already gathered training data set. Still, it is highly required as the autonomous indoor navigation system should have zero errors and be highly reliable. Fig. 8 briefs the navigation process of an autonomous indoor navigation system through a flowchart diagram. At least six different interfaces are typically trying to take part in the overall autonomous navigation system.

It starts with the sensing part, including the required sensors for extracting the raw input data required for the system, namely the odometry details, the speed with which the system is navigating, and the radio elements involved in the IPS used in general.

The following interface involves the perceptions involved, localizing the immediate surrounding, observing the obstructions present to avoid collisions, and trying to perceive the next desired pose for further navigation. The next important interface is related to navigation, wherein the complete control unit of the system and the path determination or routing functionality are included. The other interface includes the general services required, such as the inter-process controls, storing useful and processed data, etc.

The following interface controls the system's most fundamental units, the ts of systems, the stering, and bystem. The other interface required is the user end interface, including the GUI, displaying the data required by the user. Fig. 9 above describes the complete picture of the virtual interfaces required for an autonomous indoor navigation system.

4. Gradient descent algorithm

The knowledge-informed autonomous systems are trained based on the gradient descent machine learning algorithm in general [15–17]. The gradient descent algorithm stays as the base of the training algorithm in our suggested system as its functions as the core optimization algorithm, wherein optimization lies as the explicit aim of any technology-based real-time application like our autonomous indoor navigation system, for instance.

Saying it in mathematical terms, a gradient descent algorithm aiming at optimization is an iterative algorithm of first order arriving at the local minimum of a given differentiable function. For the given machine learning-based model built, the deviation in the values of the predicted ones by the system and the detected real-time ones, we call the cost function.

As justified, any real-time model expects its cost function to be as minimum as possible. The gradient descent algorithm helps find the model's coefficients in such a way that its cost function is at its minimum value possible. Hence, this algorithm is found attractive allowing it with many variations [25].

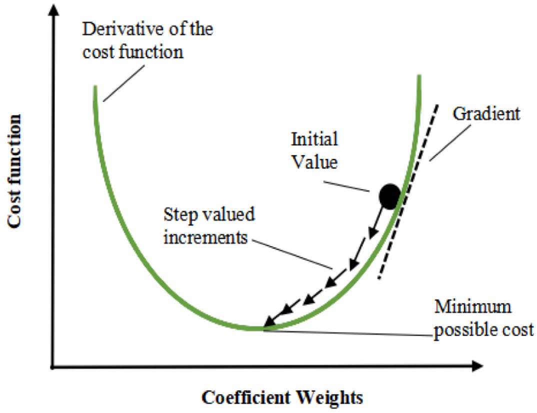

Fig. 10. Concept of Gradient Descent Algorithm

The procedure of the gradient descent algorithm is given below:

1) Assume the coefficient of the function mapping the input and the output to some minimal random value closer to zero.

$$\mathrm{coeff} = 0.0 \tag{1}$$

2) The cost of the function is calculated by modeling the given coefficients into a function.

$$\mathrm{cost} = \mathrm{f}(\mathrm{coeff}) \tag{2}$$

3) The derivative of the cost function or the slope value is calculated to compute the direction of the coefficient values computed, which is heading towards a lesser value in the next iteration [24].

$$\Delta = \mathrm{der}\ (\mathrm{cost}) \tag{3}$$

4) The rate of learning, or the amount the coefficients could change with each iteration, is given by α.

$$\mathrm{Coeff} = \mathrm{coeff} - (\alpha * \Delta) \tag{4}$$

5) The steps are repeated such that the computed coefficient value becomes equal to or almost equal to zero.

The application of the gradient descent algorithm to our machine learning algorithm is made by estimating an appropriate target function. The target function is the one that maps the given input data to the desired output as expected in real-time. This requires a certain number of weighting factors called coefficients such that the target function is precisely computed, as shown in Fig. 10.

The gradient descent algorithm helps fine-tune the coefficients by being a suitable optimization algorithm by itself and refines the target function in a much more efficient way. The algorithm arrives at a prediction value of the target function of the given model for every instance of the training data set value. It compares it with the actual output values and infers the deviation error, summing it up to form a sum error called the cost function.

The derivative of the cost function is obtained, and the steps, as stated before, are continued to find the coefficients. Each iteration termed a batch involves calculating the cost for every training data set entry, hence called the batch gradient descent method.

If the data set involved is huge enough, the stochastic gradient descent method is used.

In this method, the order of the training data set is done in a random manner, and the value of the coefficients is updated for every instance of the data set value rather than summing it up for a batch of data set as before. It is a much faster method of training for huge data set applications.

If the input is $X = [x_1, x_2, .., x_z]$ and the mapped output is Y, then a function f(x) is the predicted model that tries to map the input X to the desired output Y as accurately as possible. The value of residue or error calculated in terms of the Sum of Squared Residuals (SSR) is given by-

$$\mathrm{SSR} = \Sigma_i (y_i - f(x_i))^2 \tag{5}$$

The lower the SSR value, the better the prediction is made by the module chosen.

SSR's value is minimized by adjusting the weighting coefficients' values. The general representation of the function f(x) is given by,

Table 1
Simulation Parameters

Attributes	Parameter Values
SLAM type	lidar SLAM
Sensing distance	6 cm
Number of scans	10
Map resolution	20
Gradient Descent type	Stochastic Gradient Descent algorithm
Learning rate	0.001,0.01 and 0.1
Number of iterations	120

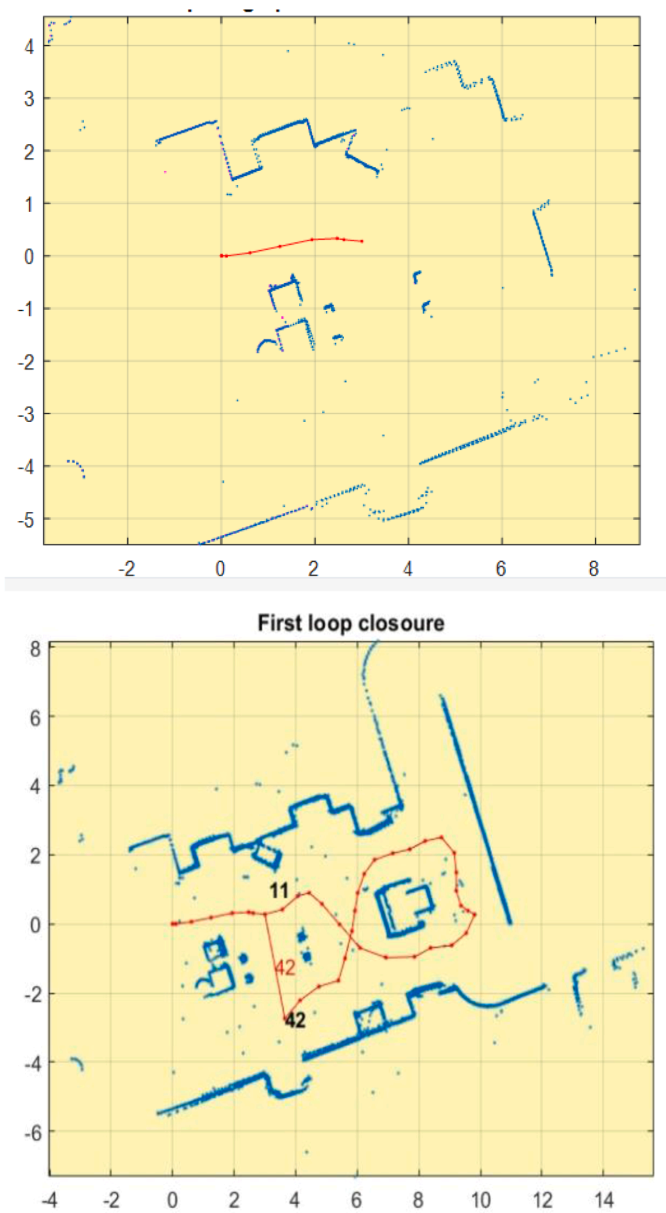

Fig. 11. (a): Initial Pose graph. Fig. (11.b): Raw Map - Complete. Fig. (11.c): Completed Map - Final. Fig. (11.d): Grid Map showing the Occupancy.

$$f(x) = w_o + w_1x_1 + \ldots + w_zx_z \tag{6}$$

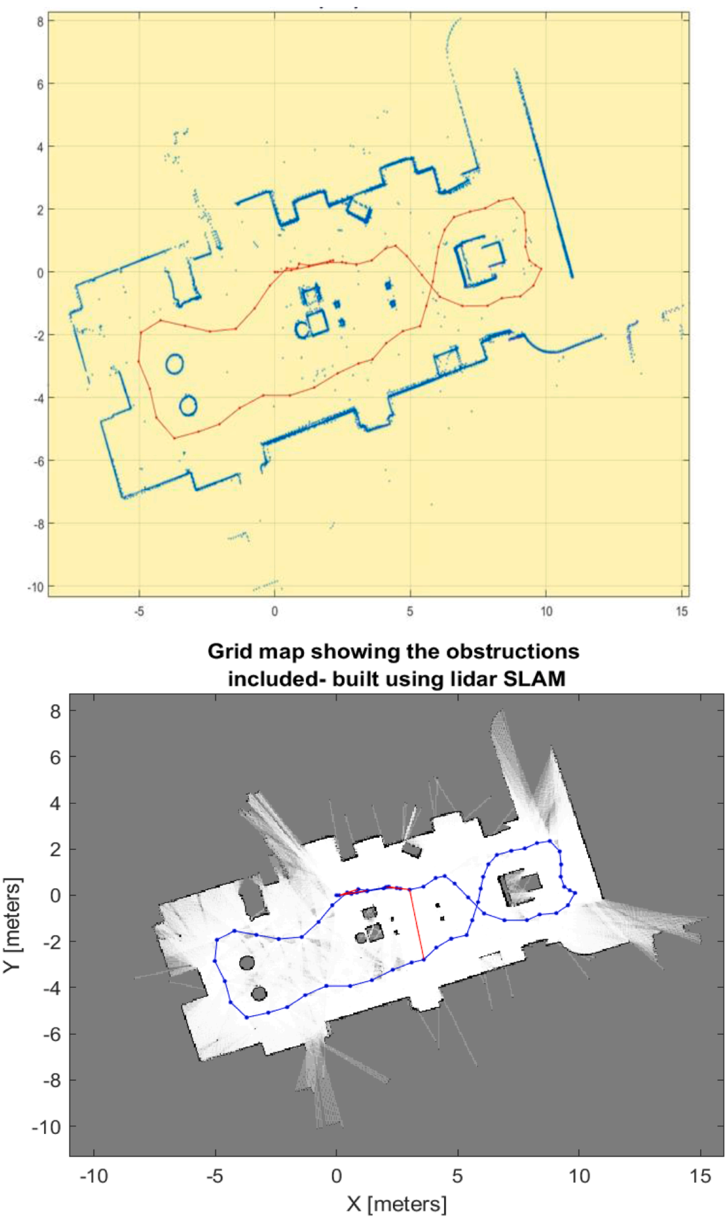

Fig. 11. (*continued*).

So, the values are chosen for $w_o, w_1,\ldots,w_z$ is such that the SSR value computed is minimized almost to zero.

If the output takes up a value like TRUE or FALSE, then the cross-entropy function for the given input-output mapping must be minimized. The cross-entropy function is given by,

$$H = -\sum_i (y_i \log(p(x_i)) + (1 - y_i)\log(1 - p(x_i))) \quad (7)$$

If it is a batch gradient descent method of implementation, the SSB is calculated at every instance of the training data for the complete batch, and then the update in the coefficients is done, And in the case of a stochastic gradient descent method of implementation, the update in

Coefficients are done for every new prediction being made and compared with real value in finding the residue value.

5. Simulation results and discussions

The suggested model of the autonomous indoor navigation system with an informed machine learning technique is simulated such

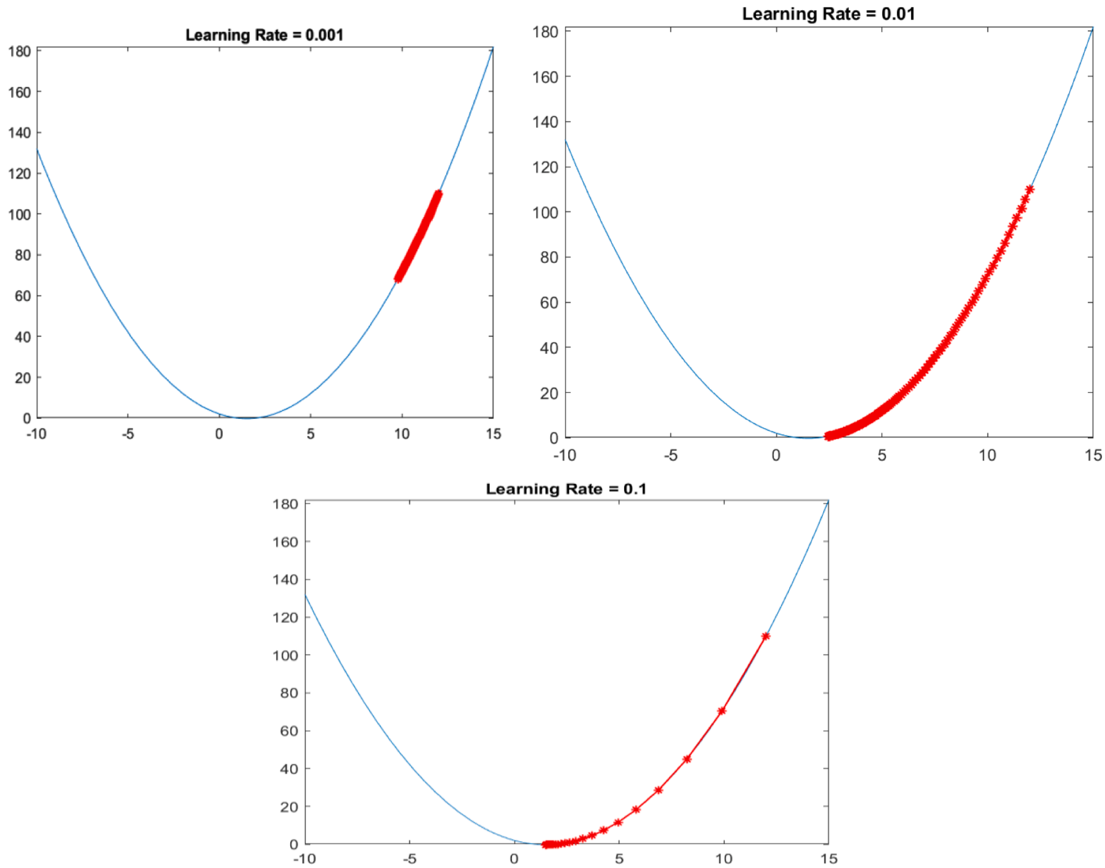

Fig. 12. (a): Learning Rate, α = 0.001. Fig. (12.b): The learning rate, α = 0.01. Fig. (12.c): Learning Rate, α = 0.1

that the navigation system is designed based on SLAM technology, and the training of the system is based on informed machine learning, which in turn is optimized using a gradient descent algorithm. The indoor mapping and routing of the traverse paths are done using lidar SLAM by measuring the odometry values and processing them.

Some of the factors taken into account in the straightforward simulation model of an autonomous indoor navigation system based on informed machine learning approach are listed in Table 1 above.

Fig. (11.a) shows the initial pose graph trying to map the surrounding environment based on the first 10 scans of the lidars. Fig. (11.b) shows the fully mapped initial view of the surrounding. And Fig. (11.c) shows the completed map in its final view by the system.

The above Fig. (11.d) shows the occupancy details of the surrounding including the obstructions present in the environment of observation.

The training optimization algorithm based on Stochastic Gradient Descent algorithm is greatly influenced by the learning factor value being chosen. The suitable learning factor value being chose, helps in better and faster convergence of the system.

When the value of $\boldsymbol{\alpha} = \mathbf{0.001}$, the graph clearly shows the training process is not nearing to its proper convergence towards the desired cost minimum value.

When the value of the learning rate, $\boldsymbol{\alpha} = \mathbf{0.01}$, the system slowly converges towards the local minimum but the number of steps taken is more in number making the process a little laborious.

The above Fig. 12.a, 12. b, and 12. c show that when the learning rate is chosen to be α = 0.1, the system model tries to converge to the local minimum in a better way and the number of steps involved goes in a steady making the model effective in achieving the lowest possible cost function for that matter. Hence, choosing the value of the learning rate is highly essential and a factor called Momentum is made use of in the optimal selection of the value of **α**.

6. Conclusion

In this research, we proposed and explored an informed machine learning technique to enhance the performance of an autonomous indoor navigation system. By incorporating additional information alongside the traditional training data, it overcomes the limitations of conventional machine learning algorithms. Our study focused on developing an efficient and cost-effective approach using a simulated environment based on lidar SLAM. The optimization of the proposed system model's training process was achieved through the utilization of the stochastic gradient descent algorithm. The choice of the learning rate (α) played a crucial role in determining the convergence rate of the system. We observed that setting α = 0.1 resulted in a better and steadier convergence to the local minimum, enabling the system to achieve the lowest possible cost function. This finding highlights the effectiveness of our suggested model in generating accurate virtual interfaces essential for autonomous indoor navigation. The simulation results demonstrated the efficacy of our approach in ensuring collision-free paths for robot or unmanned aerial vehicle navigation indoors. The system successfully performed indoor mapping and routing by processing odometry values acquired through lidar SLAM. Through the integration of informed machine learning technique, the proposed system exhibited higher autonomy and efficiency. While our study was conducted in a simulated environment to optimize resources, we recognize the importance of conducting future research in real-world indoor environments. The transition to real-world scenarios will validate the practical applicability and robustness of our approach. Overall, the presented informed machine learning technique holds great promise in advancing autonomous indoor navigation systems. Its ability to incorporate prior knowledge and additional data enables the system to make well-informed decisions, ensuring safe and efficient navigation in complex indoor settings. We believe that our work contributes to the growing body of research in the field of autonomous robotics and opens up new possibilities for real-world implementation.

Data availability statement

No data were used to support this study.

Funding statement

The authors receive no external funding for this research

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.

Data availability

No data was used for the research described in the article.

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