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Mobile Robot Intelligence Based SLAM Features Learning and Navigation

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Abstract: For efficient, and knowledge based navigation, it is essential to blend mobile robot navigation details with information and details from navigation paths-localities. In this respect, the presented scheme was focused towards building intelligence for mobile robot navigation. Intelligence was achieved by considering the navigation capabilities while the mobile robot was in motion. The adopted learning paradigm was a five layers Neuro-Fuzzy learning architecture, with to ability to create an FIS inference for enhanced navigation. To capture the enormous visual and non-visual sensory data, the mobile robot platform has fully computer-interfaced stereo vision, and reliable 3D perception system onboard the mobile platform. A Neuro-Fuzzy intelligence paradigm was used to learn navigation maps (SLAM) main visual features, distances, nature of localities as it travels within spaces. Blinding intelligence with visual maps and non-visual sensory data, has indeed resulted in improved navigation capabilities.

Keywords: Mobile Robots, Maps Learning, Neuro-Fuzzy FIS, Intelligent Navigation, Visual Perception, PAC.

1. INTRODUCTION

A. Visual Navigation

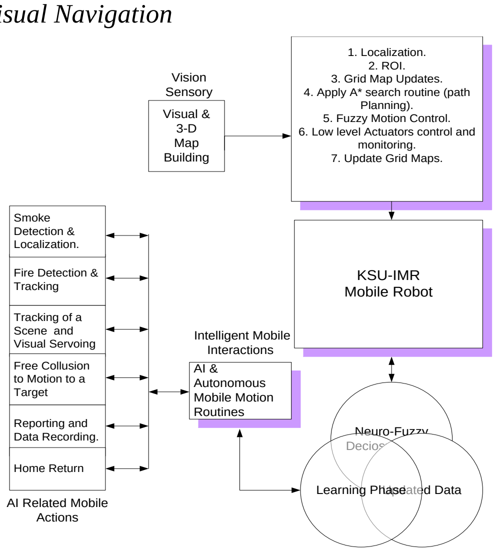

Figure 1. Intelligence navigation hierarchy for the KSU-IMR project.

Visual information are used much more than other nonvisual data. Such a concept was introduced world-wide. It was emphasized that, in order to achieve human-like quick eye movements and image processing for intelligent mobile robot path planning, high speed stereo vision system is to be developed. Mobile robots are needed to understand the surroundings intelligently, Fig.1. There are considerable efforts to make mobile robots to function intelligently within unknown, unstructured environments with intelligent behaviors, [1],[2],[3],[4],[5],[6]. Kumar and Dhama in [7], described that a fuzzy logic controller with a set of certain rules is used to obtain a goal reaching task. They stated that, "a neural network is conceived to control robot actuator system by adopting feed forward back-propagation supervised learning strategy". Hani et al. [8] have indicated how mobile behavior can be coordinated with other behaviors that receive immediate reinforcement learnt during previous work to generate an intelligent reactive navigator, that can deal with unstructured and changing outdoor environments. They added, "system described uses a lifelong learning paradigm whereby it is able to dynamically adapt to new environments and update its knowledge base", Hani et al. [8]. Similar research outcomes are also found in [9],[10],[11]. In Petru et al. [12], a neuro-fuzzy controller for sensor-based mobile robot navigation in indoor environments was also presented. The control system consists of a hierarchy of robot behaviors. Sebastian in [13], also mentioned that "topological maps are generated on top of the grid-based maps, by partitioning the latter into coherent regions. By combining both paradigms, the approach presented here

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gains advantages from both worlds: accuracy/consistency and efficiency", Sebastian in [13]. Smith and Gelfand [14], Wei et al. [15], have presented a neuro-fuzzy system architecture serving as a behavior-based control of a mobile robot in unknown environments. ANN was trained to recognize the environment, then plan a motion.

B. Maps Learning

Janglová in [16], describes an approach for solving the motion-planning problem for mobile robots control using neural networks-based technique. Janglová stated "our method of the construction of a collision-free path for moving robot among obstacles is based on two neural networks". Janglová proposed a head ANN and is used to determine the "free" space using ultrasound range finder data. The subsequent ANN "finds" a safe direction for the next robot section of the path in the workspace while avoiding nearest obstacles. Janglová used ANN minimization of average squared error cost function E_{avg} Eq. (1):

$$E_{avg} = \frac{1}{n}\sum_{n=1}^{n}\frac{1}{2}\sum_{j=1}^{v}\left(d_i(n) - y_i(n)\right)^2 \quad (1)$$

In terms of advanced maps building with visual mobile robot capabilities, a remote controlled, vision guided, mobile robot system is introduced by Raymond et al., [17]. The drive of this research work, is to describe exploratory research on a design of the remote controlled emergency stop and vision systems for an autonomous mobile robot. The mobile robot BEARCAT was built for the Association for Unmanned Vehicle Systems AUVS 1997 competition. The robot has full speed control with guidance provided by a vision system and an obstacle avoidance system using ultrasonic sensors systems. Vision guidance is accomplished using (two CCD) cameras with zoom lenses. Camera modeling and distortion calibration for mobile robot vision was also introduced by Gang et al., [18]. In their paper they present an essential camera calibration technique for mobile robot, which is based on Pioneer II experiment platform. The technique includes transformation of coordinates system for vision system, the model and principle of image formation, camera distortion calibration. Because of the non-linear distortion of camera, algorithm with optimizing operators is presented to improve calibration precision.

In reference to Bonin-Font et. al. [19], they focused their work towards two major approaches: map-based navigation and mapless navigation. Map-based navigation has been in turn subdivided in metric map-based navigation and topological map based navigation. Bonin-Font et al. [19] stated, "our outline to mapless navigation includes reactive techniques based on qualitative characteristics extraction, appearance-based localization, optical flow, features tracking, plane ground detection/tracking, etc...".

Atsushi et al. in [20] have developmental a high speed vision system for mobile robots. In their work, it was emphasized that, an image sensor is separately developed, which corresponds to the photoreceptor layer of the layered vision chip. The image sensors are tentatively mounted on the camera head, since the resolution of the prototype of the layered vision chip was not sufficient. Head camera has an azimuth DOF for each eye and a common elevation DOF. Camera weight of the head is strictly limited, since it is mounted on a mobile robot. In order to satisfy both demands for the quick movements and light weight, the camera head is designed based upon a simple parallel mechanism.

Abdul et al. [21] have introduced a hybrid approach for vision based self-localization of autonomous mobile robots. They present a hybrid approach towards self-localization of tiny autonomous mobile robots in a known but highly dynamic environment. The proposed algorithm is intended for two-wheeled differential drive robots which are equipped with a pivoted stereo vision system, two digital encoders, a gyro sensor, two (10g) accelerometers and a magnetic compass. Tracking of the globally estimated position is performed within the framework of extended Kalman filter.

C. Fuzzy Representations of Maps

Ho-Dong et al. in [22] have also introduced an augmented reality mobile robot based vision system. In their paper, they introduced a tele-presence vision system for monitoring of a network based mobile robot. The vision system was a vision part of human machine interface with augmented reality for the network based mobile robot. They synchronize head motion of human user and the camera motion of the mobile robot using visual information, user of the mobile robot can monitor environment of the mobile robot as eyesight of mobile robot. In [23], Filliata and Meyer, stated that, "map-based navigation systems are categorized according to a three-level hierarchy of localization strategies, which respectively call upon direct position inference, single-hypothesis tracking, and multiplehypothesis tracking. They stated the advantages and drawbacks of these strategies". A typical review ANN approach reported by Filliata and Meyer [23].

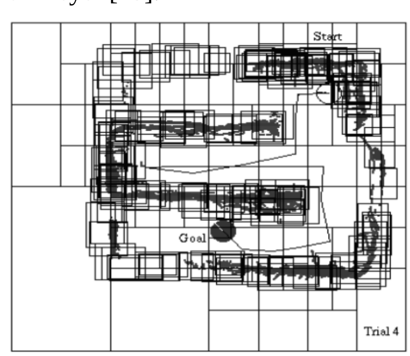


Figure 2. Learning maps and dynamic spaces, Araujo [24].

In [24], as illustrated in Fig. 2, Araujo has presented a fuzzy ART neural architecture for robot map learning and navigation. Araujo proposed methods that are integrated into a navigation architecture. Araujo [24], also stated that, "with the new navigation architecture the mobile robot is able to navigate in changing worlds, and a degree of optimality is maintained, associated to a shortest path planning approach implemented in real-time over the underlying global world model". For demonstrating the feasibility and effectiveness of the proposed methods, a number of experimental results were attained for a (Nomad 200) mobile robotic system.

Development and integration of generic components for a teachable vision-based mobile robot is introduced by Tomohiro et al. [25]. In their efforts, they presented a mobile robotic system for human assistance in navigation- the robot navigates by receiving visual instructions from a human being and is able to replicate them autonomously. They described three generic components defined as the HOST, the VISION, and the CONTROL components as well as their integration in the teachable mobile robot. Each component is described with a peculiar feature of extensibility. Especially in the VISION component, there are two major features. The first was a correlator which each vision board possesses. The correlator does block-matching between the templates and the grabbed images in real-time. The other is the PIM library which manages the visual tasks over limited parallel visual resources of the mobile robot.

Skill acquisition of a ball lifting task using a mobile robot with a monocular vision system was also introduced by Ryosuke et al. [26]. The work presents a basic examination of skill acquisition of a ball lifting task using a mobile robot with a monocular vision system. Ball lifting is considered as a basic practice in sports such as tennis or soccer. They examined the performance of a robot system and demonstrated that the robot performs the task in spite of many difficulties. The purpose is to develop an intelligent robot system that performs a human skill, they have built a basic but significant robot system as a first step.

D. Kohonen's SOM , Map Memorization

In reference to navigation maps memorization, there are a number of research outcomes, in this sense. The main objectives, are to let the mobile robot remembers the routes, locations, in addition to different information related to the spaces it moves through.

In [27], Vlassis et al., motioned in their paper, "present a method for building robot maps by using a Kohonen's self-organizing artificial neural network, and describe how path planning can be subsequently performed on such a map. We show that our method can also be applicable in cases of a pre-existent CAD of the environment".

Stereo vision-based autonomous mobile robot was given by Changhan et al. [28]. In their research, they proposed a technique to give more autonomy to a mobile robot by providing vision sensors. The proposed autonomous mobile robot consists of vision, decision, and moving systems. The vision system is based on the stereo technology, which needs correspondence between a set of identical points in the left and the right images. Though mean square difference is generally used for the measure of correspondence, it is prone to various types of error caused by: shades, color change, and repetitive texture, to name a few. Edge of object is first extracted from the Laplacian of Gaussian (*LoG*) filtered image and post-treatment is performed to eliminate remaining high-frequency noise.

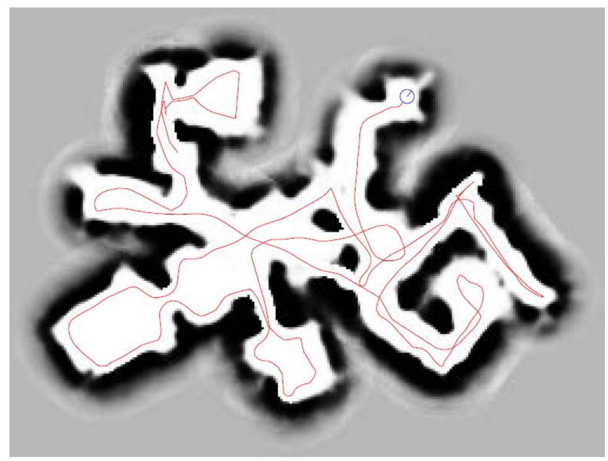


Figure 3. Learning maps and dynamic spaces, Thrun [29].

In reference to [29], Thrun reported and described an approach that integrates both paradigms: grid-based and topoIogica1. Thrun stated that, "Grid-based maps are learned using artificial neural networks and naive Bayesian integration, as referred to in Fig. 3. Topological maps are generated on top of the grid-based maps, by partitioning the latter into coherent regions. By combining both paradigms, the approach presented here gains advantages from both worlds: accuracy/consistency and efficiency. Their paper gives results for autonomous exploration, mapping and operation of a mobile robot in populated multi-room environments". Intelligent real time control of mobile robot based on image processing was also given by Nima et al. [30]. In this research a control scheme has been proposed for the first time to control a mobile robot using fuzzy control and image processing approaches in two cascaded loops. Nima et al. [30] also reported that, "the image processing approach is used to estimate the traveled trajectory and configuration-defined as velocity and azimuth- of the mobile robot using special landmarks. Having appropriate feedbacks, the fuzzy controller is used to control the mobile robot at the desired configuration while traveling to the destination point".

E. Research Contribution, and Paper Outline

This research structure is highlighting a number of issues related to use of Neuro-Fuzzy learning for improving navigation tasks (mobile robot within hazardous localities). This includes the usage of navigation maps and SLAM updates, maps learning, hence to use enormous routes information for improved navigation. This involves also the use of a five layers neural network for achieving the learning scheme. In this respect, this article has been organized into FIVE main sections. In section (*i*), we introduced the concept of navigation maps learning. Different approaches have been summarized in this respect. Section (*ii*) presents the essentials of optimal route search used for mobile robots navigation systems, this includes occupancy grids, optimal route search. In section (*iii*), SLAM system, and other related routines are also presented. Hence, Section (*iv*) presents few important issues related to the adopted and used learning paradigm, which is the Neuro-fuzzy. Section (*v*) presents the experimentations space, and few related results. Finally in Section (*vi*), we draw few conclusions remarks.

2. Optimal Maps Search

A. KSU-IMR Layout and Hierarchy

The mobile robot system is intended to achieve the following foremost tasks. First is entirely related to building vision system. Second is associated with building navigation intelligence. Third is related to housing a hybrid system integrating a visually maneuvering system with defined intelligence capabilities. Maps and grids are used to build the mobile intelligence. The KSU-IMR was achieved while incorporating the FOUR MAIN interrelated functionalities, Fig.1. A decision based Neuro-fuzzy employed architecture has to be trained with mobile routes training patterns. It is a five layers system. It learns the navigation behavior, as in reference to some learned and trained patterns. Training patterns are therefore generated via grids and maps generated during navigation experimentation.

B. Mobile Robot Optimal Path Search.

For generating the most suitable maps, (SLAM learning), in this section we shall place more focus on the underlying theorem behind the adopted A^* search. For choosing mobile optimal path, the known A^* search algorithm was adopted. Along mobile motion, the search algorithm passes through mapping graph, it then surveys for the best path of a lowest known cost, while updating a sorted priority queue of different path divisions. In its basic principle, in a continuous search till a final goal is found, during a traversing of a mobile detected map, a section of a path being traversed would be given a higher cost than another encountered path segment. It leaves the higher-cost path segment and continues to search for lower-cost path sections. A^* relies on the concept of (best-first search and finds a least-cost path) from an assumed mobile robot initial posture to the mobile goal posture.

Denoting $f(x)$ as "Distance-Plus-Cost heuristic" function, A^* uses $f(x)$ to decide the direction in which the search visits mobile posture in a tree. DPC is a summation of two parts. (*i*): A path-cost function. This is a cost from an initial mobile robot posture to the present posture, $g(x)$. (*ii*): A "heuristic estimate" for the distance to the mobile desired posture, as named by $h(x)$. The $h(x)$ term of the $f(x)$ function must show an admissible heuristic. It not essential to overestimate the distance to the goal. Using A^* in mobile robot routing, the function $h(x)$ *is* characterized by a straight-line distance to a ending mobile goal. If heuristic $h(x)$ satisfies an additional condition $(h(x) \le d(x,y) + h(y))$ for every edge (x,y) of the graph (where d denotes the length of that edge), in this respect, $h(x)$ is known to be consistent. For such a case, A^* can assume an effect implementation, i.e. no node needs to be processed more than once, and A^* is equivalent to running Dijkstra's algorithm, with a reduced cost:

$$d'(x,y) = (d(x,y) - h(x) + h(y)) \tag{2}$$

A main concern of the A^* search, is related to time complexity. This is totally in dependency on the heuristic search. This can also be seen as an exponential expanding of mobile robot number of nodes, while storing information about for the shortest path. Since there is only a single goal posture the mobile must move to, the heuristic function $h(x)$ is to satisfy the following condition:

$$|h(x) - {}^{*}h(x)| = O(\log h^{*}(x)) \tag{3}$$

In Eq. (3), ${}^{*}h(x)$ is defined as the optimal heuristic, the exact cost to get from x posture to the final mobile target position. Equation (3) can be interrupted as follows: Heuristic error in $h(x)$ should not propagate faster than the logarithm of the ${}^{*}h(x)$, the BEST heuristic", which computes an accurate distance from robot initial posture (x) to a targeted posture. In summary, A^* relies on the backward costs, and forward costs, i.e. "estimates of". In its nature, it can be mentioned that, A^* is optimal with admissible heuristics.

B. Occupancy Grids: Mapping Techniques

Practically, an occupancy grid splits a space where the mobile robot to move into small discrete grids. It then assigns each grid location a numerical value. Such numerical value is associated with the probability that the location is occupied or not by an obstacle. Before mobile robot starts a manoeuvre, all assigned grid values are set to a medial value. Hence, the mobile robot sensing instrumentations supply uncertainty regions (*physical readings*) where an obstacle is expected to be detected. Grid localities within these defined regions of ambiguities, have therefore, their assigned values increased.

On the contrary, localities within a sensing pathway, more precisely the ones between the mobile robot and localities in the sensing path between the robot and the obstacle, will be assigned reduced probabilities. For constructing occupancy grid, the sensing tool (used visual sensing) has to be correctly modelled. In this context, Murray and James in [31] have been indicated that, "experiments with sub-pixel interpolation indicate that the Triclops stereo vision module produces results with standard deviations well below one pixel". In order to reduce the sensing computational time, and for real-time considerations, sub-pixel interpolation have not been used within such stereo algorithm. We can still approximate a model for the mobile robot stereo vision by the adopting an approximated relation:

$$\begin{aligned} &P(d \mid \beta)=1 \quad \text{For} \quad \beta=\beta(d+0.5)\rightarrow\beta(d-0.5) \\ &P(d \mid \beta)=0 \quad \text{Otherwise} \end{aligned} \tag{4}$$

In Eq. (4), we defined a relation of navigation image disparity d to depth β as:

$$\beta(d)=\left(\frac{f\gamma}{d}\right)\beta \tag{5}$$

In Eq. (5), γ is the baseline between the two cameras, whereas d is the disparity. We need to shift from one dimensional vision to two dimensional. This is done via stereo triangulation technique. For each individual pixel, resulting from the pair of cameras, stereo triangulation is therefore a result of intersection of the lines of sight. The stereo triangulation technique is used to create a two dimensional position of an obstacle in front of the mobile robot. This is based on a particular pixel (i) over an image of a reference camera and resulting a disparity result d from stereo matching.

Further analysis of lines of sight for centres of two pixels shows there is an error bound, this is as a result of "diamond" shape around a position. It resembles an elliptical area used as a model by Murray and James, as in [31]. In reference to the geometry of triangulation Guilherme and Avinash [32], it is needed to evaluate (for a given pixel and disparity), a region of uncertainty. For a trapezoidal region of uncertainty, associated corners are evaluated by calculating the area β, where $\beta=\beta(d\pm 0.5)$, hence calculating $X=\left(\frac{(x\pm 0.5)\beta}{f}\right)$. Here (x) is an image plane coordinate alongside the rows of an image, in addition, f is the camera focal length. Hence, an unoccupied area, for which an obstacle should not appear, is in fact a triangular as shaped by the robot's posture, and the closest two corners of the trapezoid.

3. Mobile Robot SLAM System

We shall denote a state of mobile robot as $X_{ij}(k)$. While manoeuvring, dynamical motion of a mobile robot can be modelled by linear discrete-time state transition equation. This is expressed by state equation of Eq. (6):

$$X_v(k+1)=F_v(k)x_v(k)+u_v(k+1)+V_v(k+1) \tag{6}$$

In Eq. (6) $F_v(k)$ is the state transition matrix, $u_v(k)$ is the control inputs, and $V_v(k)$ is the uncorrelated mobile dynamics noise errors, as expressed with zero mean and covariance $Q_v(k)$. We shall also name locality of an i^{th} feature (landmark), by p_i. Hence, defining a state transition matrix of an i^{th} observed feature is expressed as:

$$p_i(k+1)=p_i(k)=p_i \tag{7}$$

we shall let the number of features (landmarks) of a size N vector, as they are stationary features. A vector of all N landmarks is:

$$p=\begin{pmatrix}p_1^T & p_2^T & \cdots & p_N^T\end{pmatrix}^T \tag{8}$$

Extending state vector $x(k)$ to contain also state vectors of the localities *visual features*. This is also denoted by:

$$x(k)=\begin{pmatrix}x_v^T(k) & p_1^T & \cdots & p_{N-1}^T & p_N^T\end{pmatrix}^T \tag{9}$$

This leads to the following entire mobile robot and features state transition model:

$$\begin{pmatrix}x_v(k+1)\\ p_1\\ p_2\\ p_{N-1}\\ p_N\end{pmatrix}=\begin{pmatrix}F_v(k) & 0 & 0 & \cdots & 0\\ 0 & I_{p1} & 0 & 0 & 0\\ 0 & \vdots & I_{p2} & 0 & 0\\ \vdots & \vdots & \vdots & \ddots & 0\\ 0 & 0 & 0 & 0 & I_{pN}\end{pmatrix}\begin{pmatrix}x_v(k)\\ p_1\\ p_2\\ \vdots\\ p_N\end{pmatrix}+\begin{pmatrix}u_v(k+1)\\ O_{p1}\\ O_{p2}\\ \vdots\\ O_{pN}\end{pmatrix}+\begin{pmatrix}V_v(k+1)\\ O_{p1}\\ O_{p2}\\ \vdots\\ O_{pN}\end{pmatrix}$$

$$x(k+1)=F(k)x(k)+u(k+1)+v(k+1) \tag{10}$$

In Eq. (10), I_{p1} is an $\Re^{(pi)\times(pi)}$ identity matrix. In addition, matrix O_{p1} is the dim(p_i) null vector.

Mobile Robot Motion Predication Phase:

In reference to mobile robot body allocated frames, and for the case of ${}^{i}C$ as a vector of coordinates of an i^th^ defined landmark. There are k landmarks. As state vector, this is defined by:

$$S_t = \left(x(t), y(t), \theta(t), {}^{1}c_t^T, \cdots {}^{k}c_t^T\right)^T.$$

For the POWERROB (KSU-IMR project) mobile robot system, it is equipped with $(\Delta\theta_R, \Delta\theta_L)$ measurement, i.e. differential drive in which are the right and left angular displacement of the respective wheels are known or measured. For instance, if the mobile robot wheels rates are considered constant during one sampling period, we can decide on the mobile motion kinematics geometric models. This is further expressed as:

$$\begin{pmatrix} x(t) \\ y(t) \\ \theta(t) \end{pmatrix} = \begin{cases} (x_{t-1}) + \left(\dfrac{\Delta L}{\Delta\theta}\left(sin(\theta_{t-1} + \Delta\theta) - sin(\theta_{t-1})\right)\right) \\ (y_{t-1}) - \left(\dfrac{\Delta L}{\Delta\theta}\left(cos(\theta_{t-1} + \Delta\theta) - cos(\theta_{t-1})\right)\right) \\ \theta_{t-1} + (\Delta\theta) \end{cases} \quad (11)$$

In Eq. (11), $(\Delta L, \Delta\theta)$ are representing the linear and angular displacement of the mobile robot. In terms of mobile physical parameters, they are also expressed by:

$$\begin{cases} \Delta L = \dfrac{(\Delta\theta_R r_R + \Delta\theta_L r_L)}{2} \\ \Delta\theta = \dfrac{(\Delta\theta_R r_R + \Delta\theta_L r_L)}{\ell} \end{cases} \quad (12)$$

MAP Model Updating layer: While building a MAP, this entirely dependent on voxels. However, this needs to updated the state of each voxel by adopting $(K_{(i,t)} : 0 \leftrightarrow 1)$ a credibility value. In this sense, such a credibility measure defines a degree to trust a given observation $O_{(t)}(V_i)$ of the voxel (i) calculated based on the stereo pair taken at a time instant (t). Such a map update is computed based on time index consideration, i.e. for a defined time t, and for an updated occupancy observation $O_{(t+1)}(V_i)$, the corresponding voxel (state) is updated by:

$$\begin{pmatrix} S_{(t+1)}(V_i) \\ S_{to}(V_i) \end{pmatrix} = \begin{cases} (1 - k_{i,t+1})S_t(V_i) + k_{i,t+1}O_{t+1} \\ 0 \end{cases} \quad (13)$$

$K_{(i,t)}$ is depending on a number of time varying terms. This dependency does include determined voxel neighborhood homogeneity, quantity of preceding measurements, the period of last observation. Already occupied voxel is not likely to be found in an otherwise empty environment. Therefore, measurements demonstrating homogeneous sections, are further expected to be (credible) and we don't want to trust the very first measurements and over aged measurement at a point too much. If $O_{(t)}(V_i)$ is designated as neighbourhood HOMOGENEITY of an observation, hence $O_{(t)}(V_i)$ is found through a use of a set of (N) voxel within neighbourhood of (V_i). It is useful to only view directly neighbouring voxels. To achieve such a theme, Eq. (13) expresses $H_{(i,t)}$, the homogeneity of an observation at a voxel (V_i) at a time instant t.

$$H_{(i,t)} = \left(\frac{\sum V_{j\in N}\left|O_t(V_i - O_t(V_j))\right|}{|N|}\right) \quad (14)$$

Furthermore, $k_{(i,t)}$ in Eq. (14) is a credibility measure, and expressed in terms of homogeneity of observation $H_{(i,t)}$. This is defined by the following relation:

$$k_{(i,t)} = \left(\frac{N_{(i,t)}(1 - H_{(i,t)})}{\sqrt{2\pi}}\right) exp\left(-\frac{(t - t_{last})}{2\sigma^2 t_o}\right) \quad (15)$$

In Eq. (15), the term $N_{(i,t)}$ is representing counts of preceding observations. $N_{(i,t)}$ is evaluated for $V_{(i)}$, the voxels, where such calculations continuous over the time (t). Furthermore, in Eq. (15), (t_{last}) is the time of last observation, as evaluated for the voxel $V_{(i)}$, and σ is representing a constant for scaling. Meta information (previous observations age, prior observations counts), are important data to be updated, such updates are stored in each voxel. For experimentation purposes, we shall show the laboratory ground used for building the map. Furthermore, we shall indicate to the representation of the states of voxels in a 3D scene for similar analysis of laboratory ground.

B. Monte Carlo Localization Layer

Within is research, we have used the Stereo vision based Monte Carlo Localization (MCL) as a primary layer for the localization parameters estimation. In sampling-based methods, we represent the density $p(x_k \vdots Z^k)$ by a set of N random samples or particles $S_k = \{s_k^i, i = 1 \cdots N\}$ drawn from it. We are able to achieve this, due to the essential duality between the samples and the density from which they are generated. From the samples we can always approximately reconstruct the density, e.g. using a histogram or a kernel based density estimation technique. The goal is then to recursively compute at each time step k the set of samples S_k that is drawn from $p(x_k \vdots Z^k)$. It is known alternatively as the bootstrap filter Gordon et. al. [4], the Monte-Carlo filter, [5], or the Condensation algorithm Isard and Blake [8]. These methods are generically known as particle filters, and an overview and discussion of their properties can be found in Doucet [3]. In analogy with the formal filtering problem, the algorithm proceeds in two phases.

(*i*) *Prediction Phase*: In the first phase we start from the set of particles $S_{(k-1)}$ computed in previous iteration, and apply the motion model to each particle $S^i_{(k-1)}$ by sampling from density $p(x_k \mid s^i_{(k-1)}, u_{(k-1)})$: (*i*) for each particle $s^i_{(k-1)}$: draw one sample $s^i_{(k)}$ from $p(x_k \mid s^i_{(k-1)}, u_{(k-1)})$. A new set S'_k is obtained that approximates a random sample from the predictive density $p(x_k \mid Z^{(k-1)})$. The prime in S'_k indicates that we have not yet incorporated any sensor measurement at time k, and to draw an approximately random sample from the exact predictive probability distribution function $p(x_k \mid Z^{(k-1)})$, we use motion model and the set of particles $S_{(k-1)}$ in order to build an empirical predictive density function of:

$$p(x_k \mid Z^{(k-1)}) = \sum_{i=1}^{N} p(x_k \mid s^i_{(k-1)}, u_{(k-1)}) \qquad (16)$$

In Eq. (16), we describe a blended density approximation to $p(x_k \mid Z^{(k-1)})$. This is combining one equally weighted mixture component $p(x_k \mid s^i_{(k-1)}, u_{(k-1)})$ per sample $S^i_{(k-1)}$.

(*ii*) *Update Phase*: In the second phase we take into account the measurement z_k, and weight each of the samples in S'_k by the weight $m^i_k = p(z_k \mid S'^i_k)$, i.e. the likelihood of S'^i_k given z_k. We then obtain S_k by resampling from this weighted set: (*ii*) for $j = (1, \cdots, N)$: draw one S_k sample S^j_k from $\{s'^i_k, m^i_k\}$.

The resampling selects with higher probability samples s0i k that have a high likelihood associated with them, and in doing so a new set S_k is obtained that approximates a random sample from $p(x_k \mid Z^k)$. An algorithm to perform this resampling process efficiently in $O(n)$ time is given by Carpenter et al. [2].

After the update phase, the steps (*i*) and (*ii*) are repeated recursively. To initialize the filter, we start at time $k = 0$ with a random sample $S_0 = \{s^i_0\}$ from the prior $p(x_0)$. Over such a second phase, it is needed to use the mobile measurement model to acquire a sample S^l_k from the subsequent terms $p(x_k \mid Z^k)$. Instead we shall be using definition of (15), hence to sample from the empirical posterior density:

$$p(x_k \mid Z^{(k)}) \propto p(z_k \mid x_k)\hat{p}(x_k \mid Z^{(k-1)}) \qquad (17)$$

The coding for the Monte Carlo Localization was achieved using C^{++} layer, with linked libraries for on-board execution.

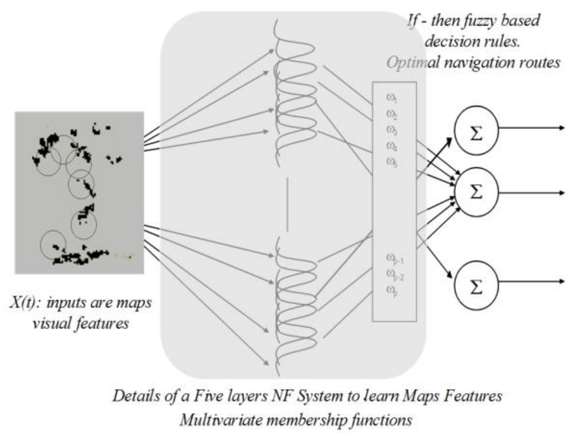


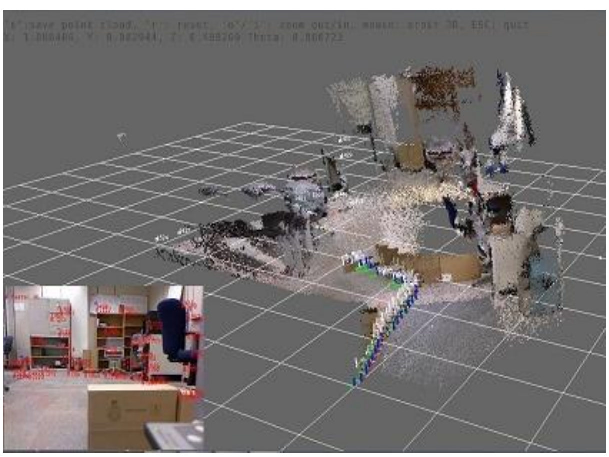
Figure 4. The built KSU-IMR five layers NF learning paradigm. It learns traversed maps main features. Inputs: (*visual maps features*). Output: (*navigation decisions*).

4. Learning Paradigm Synthesis

KSU-IMR stands for King Saud University Intelligent Mobile Robot. KSU-IMR uses a Neuro-Fuzzy system to learn the navigation maps. The final building block for the proposed navigation scheme is the learning paradigm. The synthesis of the Neuro-Fuzzy architecture, was based on using five layers, where each layer is implementing a typical fuzzy function. That was achieved while relying on five layers Neuro-Fuzzy learning structure, as illustrated in Fig. 4. Such an architecture requires a set of learning patterns. Various learning patterns were gathered from navigation maps. This is represented in terms of locations (*visual maps*), distances from obstacles (*meters*), and the nature of navigation maps. Eq. (18), is a typical linguistic fuzzy relation of a system. The fuzzy rules are consisting of the typical (*if-then*) statements. Number of inputs-outputs to the NF system, are decided by the complexity of the learning system. It consists of rules of the following form, y(*k*), A_{i1} .. Parameters are the fuzzy variables:

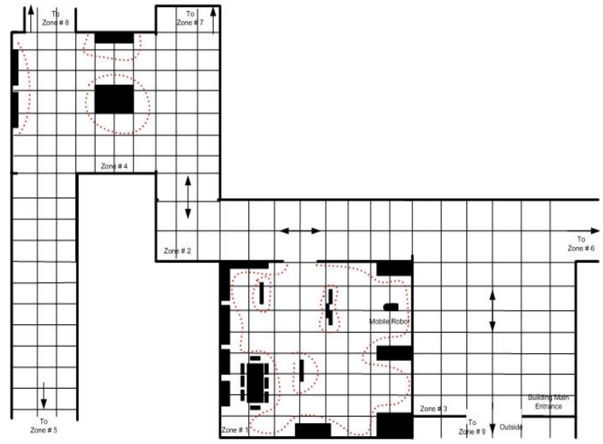
Ri : if $y(k)$ *is* A_{i1} *and* $y(k-1)$ *is* A_{i2}
and,…, $y(k-n+1)$ *is* A_{in} *and* $u(k)$ *is* B_{i1} *and* $u(k-1)$ *is* B_{i2} *and,…,*
$u(k-m+1)$ *is* B_{im} *then* $y(k+1)$ *is* C_i (18)

A complexity of the KSU-IMR Neuro-fuzzy mobile robot decision making layout has already been shown in Fig. 1. In reference to Al-Mutib et al. [33], NF has been used for making the most valid navigation decisions. This is determined upon the learned occupancy maps and optimal navigation paths, which came as results of using the SLAM routine. Learning patterns, for the NF system, are generated by letting the mobile robot move in space with obstacles around. Using the mobile stereo vision and space map already computed for using SLAM, data are gathered, with a description of the obstacles (e.g. table, chair, …), and a description of needed behaviors according. A quite large number of rules can therefore be written using the SLAM and generated map of navigation. NF has the ability of generating auto-rules, as based on numerical patterns of data. Initial memberships were defined, hence updated in shapes while receiving information, and during training phase.

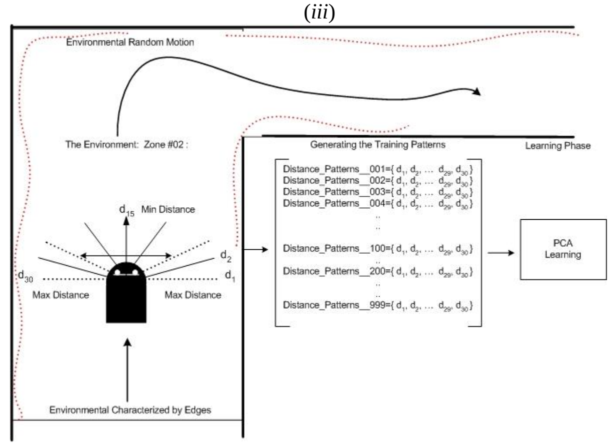


(*i*)

(*ii*)



(*iii*)



(*iv*)

Figure 5. Important Step: Creation of learning patterns. (*i*): Stereo images (the disparity map) acquired from a mobile robot during indoor navigation. (*ii*): Navigation floor. (*iii*): Zones and regions within the entire navigation building. (*iv*): Creation of training patterns, in terms of distances, and other related information and data about the navigation decisions. Navigation decisions are based on mobile posture within a learned map.

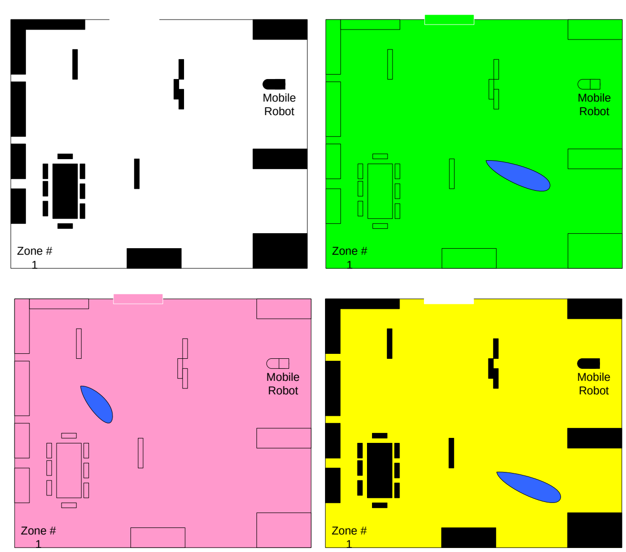


Figure 6. Dynamic navigation patterns, are to be accounted for by NF learning, due to dynamic nature of navigation environments.

There are two sets of data. The first for training, and the other one is for testing. The data sets consisted of four input-four output variables, Fig. 5, and Fig. 6:

TABLE 1: Definition of Fuzzy Inference System.

	Fuzzy Input Parameters		*Fuzzy Output Parameters*	
1	*Input #1*	*Mobile Robot Zones localities*	*Situation #1*	*Alarm Rising*
2	*Input #2*	*Mobile Robot Area localities*	*Situation #2*	*Related to Localities*
3	*Input #3*	*Zones Localities Inference (Actions)*	*Situation #3*	*Visual Focus & Defocus*
4	*Input #4*	*Zones Behaviours*	*Situation #4*	*Visual Gazing and DeGazing*

Typical inputs to learning system are summarized as follows: First stimuli {*Zone environmental identification*}: This stimuli is representing few knowledge about where the mobile system is navigating. This is defined in terms of zones. Within this study, environmental map of navigation where the mobile robot is to navigate was divided into five main zones. This is defined in terms of the following input sets:

{*Zone#1, Zone#2, Zone#3, Zone#4, Zone#5, …….Zone#k*}

second stimuli {*area of navigation*}:
This stimuli is dedicated towards the definition areas of navigation. Of a particular interest within a navigation environment is the area of mobile navigation. This tells where the mobile robot is navigating at a particular moment of time. An area of navigation is also defined within a particular zone. There are a number of areas of navigations. This could be a corridor or a hall or even any area within the defined zones, as defined below by the following input sets:

{*Obstacles in Area#1: Main_Lab_floor, Obstacles in Area#2: Out_Corridor, Obstacles in Area#3: Main_Building_Entry, Obstacles in Area#4: Main_Building_Entry, Obstacles in Area#4: Far_Left_Corrdior …… Area#m*}

third stimuli {*zone mobile related procedures*}:
Within a particular zone or area, it is needed to let the mobile robot acting with particular actions. Examples are:

{*Procedure#_1*: *Rotate_Around, Procedure#_2*: *Move_Twice, Procedure#_3*: *Scene_Video_Recordings … … Procedure#_H*: …..}

Fourth stimuli {*behaviour in hazardous*}: This stimuli is a crucial input. It defines situations when the mobile robot is detecting any hazardous activating. It takes the appropriate actions, in reference to the define hazardous situation. This stimuli do represent particular behaviours of the mobile robot, at particular locations within areas of navigations. Example of which, when the mobile robot within {zone #1, area #1}, then it is expected to have much (*gazing actions*) within this regional of interests, or it should track a scene and servo around it … and so forth ….. depending on how we define various behaviours for each zone and area within a navigation plan.

{*Behaviour#1: Gazing_Around, Behaviour#2: Toxic _Detection, Behaviour#3: Visually_Tracking, Behaviour#4: Focus_In_Out, Behaviour#5: Fire_Detection, Behaviour#n:* }

All the above defined situation, and the fined appropriate actions have already been presented in Fig. 6.

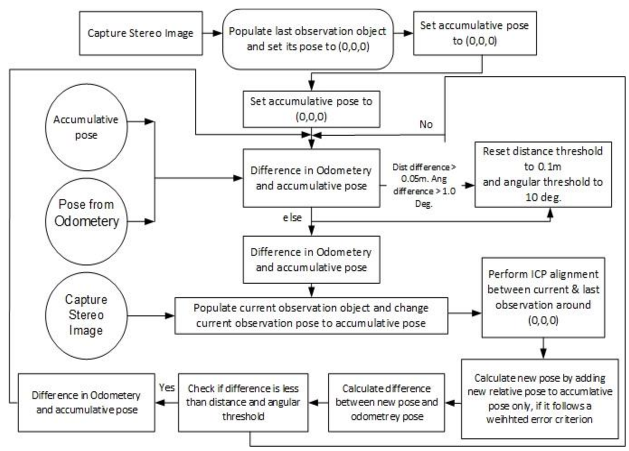


Figure 7. Iterative Closest Point (ICP) localization algorithm.

5. Results and Experimentations

A. (ICP) Based Localization

The flow chart for the employed Iterative Closest Point (ICP) localization algorithm details are presented here, as depicted in Fig. 7. A grid-based mapping approach was selected for the implementation of SLAM algorithm. Grid-resolution for the evidence map was tested with (500mm), (100mm), and (200mm) resolutions. The size of the map currently stands at (900mm^2). Mapping updates and initializations are restricted to the area under observation, which roughly was set to be (15m^2).

For map accuracy in terms of detection of small-sized obstacles and gradient floors, we have developed a customized algorithm and verify it over a number of experimentation trials. The implemented mapping module can detect a loop and propagate errors in previous poses. The grid-map cells store both the height data about the environment and also the certainty measure about the existence of an obstacle. The certainty is a function of two elements i.e. the amount of time an obstacle is observed within a cell and secondly the number of points returned by the sensor that lie within each cell. An example of a confidence map generated of obstacles in the environment (including loop detection routine) is represented in Fig. 5. Darker grid-cells represent a high probability of presence of an obstacle. Lighter shades represent an opposite hypothesis. Each observation is added to the map as a Bayesian update.

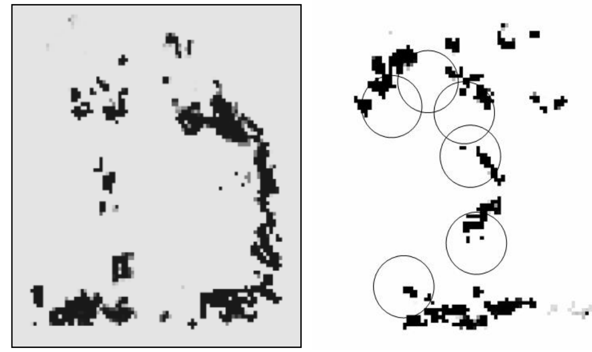
B. Map Accumulation Algorithm

The criteria for adding an observation to the built map can be defined as follows: A Bayesian update will either increase or decrease the probability of presence of an obstacle within a cell, as in Eq. (17). This probability depends upon following factors: (*i*) Presence of points lying in the cell within the current observation. (*ii*) Consecutive number of observations for which a minimum number of obstacle points can be associated to a grid-cell. Such a mechanism handles fast moving dynamic obstacles. (*a*) All cells occluded by obstacles are not updated. For this purpose only the 66^o FOV in front of camera is considered for map updates. (*b*) The obstacle height data is only used for loop-closure detection. For obstacle detection, a combination of obstacle height and their persistence over multiple observations is employed.

C. Learning Path Features, SLAM Maps

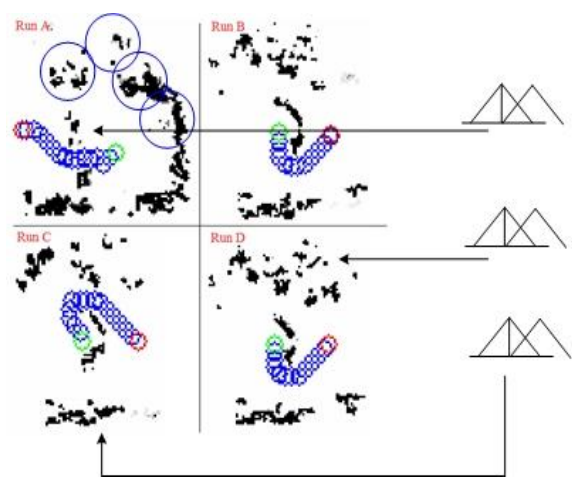
In reality, quite large of trails were successfully conducted experimentally within complex indoor obstacle scenarios for path-planning using the developed version of the Fast SLAM. The mobile robot has successfully reached its target (x,y) location using the planned paths in an autonomous approach. Furthermore, we have submitted a set of goals to our system, hence the system plans path in sections for each of the goal.

Once an obstacle scenario is significantly changed so much, in such a way that it affects the planned path, A^* algorithm is used to re-plan the path to the goal. The planning and re-planning delays are less than a time of a second long, so there exists no issue for performance degradation within path-planning module. Specifically, some of the path planning examples and runs, can be grasped in Fig. 8. In this respect, in Fig. 8 we show how a typical built intensive-features are gathered, and decisions of mobile navigation can extracted. Furthermore, in Fig. 9, we show how the features of navigation maps have been used to enhance the movement of the mobile robot, despite of its current location. (*i*): Maps, and extracting the details of environmental information. (*ii*): Typical used and resulting navigation decisions, to target manoeuvring (mobile robot path planning). The mobile robot performs various operations, depending on the area, region, and zone of navigation.

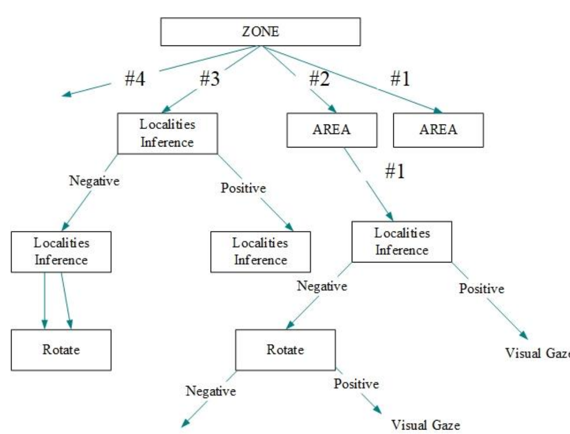


(*i*) (*ii*)

Figure. 8. (*i*) Maps generated while mobile robot in navigation phase (direct perception). (*ii*) Further details of the navigation maps data. Data are then used as further training patterns for the Neuro-fuzzy training patterns. Al-Mutib et. al. [33].



(*i*)



(*ii*)

Figure. 9. Features of navigation maps have been used to enhance the movement of the mobile robot, despite of its current location.
(*i*): Maps, and extracting the details of environmental information. (*ii*): Typical used and resulting navigation decisions, to target manoeuvring (mobile robot path planning). The mobile robot performs various operations, depending on the area, region, and zone of navigation.

5. CONCLUSION

Combining mobile robot localities - maps details with visual data gathered through a stereo vision system have been presented. Initially, real-time stereo-vision with SLAM technique were employed for navigation purposes, hence navigation training patterns (*features*) were generated. Consequently, a five layers Neuro-fuzzy system was adopted to learn navigation maps features. From hierarchy point view, the mobile robot navigation system is compromising of three fundamental layers. Within the top layer, computing and intelligence coding is located. Stereo vision related tools and routines are located within the mid-level, i.e. (*localization, mapping, maps updates, path planning, and search*). At the lower layer, navigation loops and wheels servo loops are located. It was found that, integrating a learning paradigm with such navigation data details, has resulted in extremely valuable mobile behaviours and choices that made the mobile robot intelligently navigating even at difficult localities. Due to enormous sensory and environmental information to be dealt with, we have reduced the dimensionally and size of such environmental patterns (sensory data) using PCA. The employed PCA based NF learning was achieved while learning SLAM and maps details. Reduced dimensionality of environmental information are then used as inputs to the Neuro-fuzzy. Samples of Neuro-fuzzy inputs: (*navigation zones, areas,.. and behaviours related to particular zones*).

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REFERENCES

[1] I. Batyrshin, Dragan S. Pamucar, Paolo Crippa, and Feng Liu, "The fuzzy system and its application in East Asia," (2015) Journal of Intelligent and Fuzzy Systems, 29, 6, pp. 2317-2318.

[2] J. Carpenter, P. Clifford, and P. Fernhead, "An improved particle filter for non-linear problems," Techical Report, Department of Statistics, 1997, University of Oxford.

[3] A. Doucet, "On Sequential Simulation-based Methods for Bayesian filtering," Techical Report, CUED/F-INFENG/TR.310, Department of Engineering, 1998, University of Cambridge.

J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp. 68–73.

[4] N. Guilherme, N. DeSouza and K. Avinash, "Vision for Mobile Robot Navigation: A Survey," IEEE Transactions on Pattren Analysis and Machine Intelligence, 2002, vol. (24), no. (2).

[5] J. Gordon, J. Salmond, and M. Smith, "Novel Approach to Nonlinear/non-Gaussian Bayesian State Estimation," IEE Procedings Part-F, vol. (140), no. (2), 1993, pp. 107–113.

[6] G. Kitagawa, "Monte Carlo Filter and Smoother for Non-gaussian Nonlinear State Space Models," Journal of Computational and Graphical Statistics, vol. (5), no. (1), 1996, pp. 1–25.

[7] D. Kumar, and K. Dhama, "Neuro-fuzzy Control of an Intelligent Mobile Robot," Advanced Computing & Communication Technologies (ACCT), 2012 2nd International Conf. , 2012, (7), no. (8), pp. 106-111.

[8] H. Hani, C. Victor, and C. Martin, "Learning and Adaptation of an Intelligent Mobile Robot Navigator Operating in Unstructured Environment Based on a Novel Online Fuzzy–Genetic System," Fuzzy Sets and Systems, 2004, vol. (141), pp. 107–160.

[9] M. Isard, and A. Blake, "Contour Tracking by Stochastic Propagation of Conditional density," European Conference on Computer Vision, 1996, pp. 343–356.

[10] L. Matthies and A. Shafer, "Error Modeling in Stereo Navigation, IEEE Transactions on Robotics and Automation," vol. (3), 1987, pp. 239–248.

[11] Sebastian Thrun, Learning metric-topological maps for indoor mobile robot navigation, In Artificial Intelligence, Volume 99, Issue 1, 1998, Pages 21-71, ISSN 0004-3702, https://doi.org/10.1016/S0004-3702(97)00078-7.

[12] R. Petru, M. Emil, E. Thom, A. Whalen, W. Hans, "Behavior-Based Neuro-Fuzzy Controller for Mobile Robot Navigation," IEEE Transctions on Instrumentaion and Meaurmnets, vol. (52), no. (4), 2003, pp. 1335-1340.

[13] T. Sebastian, "Learning metric-topological maps for indoor mobile robot navigation," Artificial Intelligence vol. (99), 1998, pp. 21-71.

[14] M. Smith and E. Gelfand, "Bayesian Statistics Without Tears: A Sampling-Resampling Perspective," American Statistician, vol. (46), no. (2), 1992, pp. 84–88.

[15] L. Wei, M. Chenyu, and M. Wahl, "A Neuro-Fuzzy System Architecture for Behaviour-Based Control of a Mobile Robot in Unknown Environments, Fuzzy Sets and systes," vol. (87), 1997, pp. 133-140.

[16] D. Janglová, "Neural Networks in Mobile Robot Motion," Janglová, Inernational Journal of Advanced Robotic Systems, vol.1, no.1, ISSN 1729-8806, 15-23, 2004.

[17] A. Raymond, S. Tayib, and L. Hall, "Remote controlled, vision guided, mobile robot system," Proceedings of SPIE. The International Society for Optical Engineering, vol. 3208, pp. 126-132, Intelligent Robots and Computer Vision XVI: Algorithms, Techniques, Active Vision, and Materials Handling, 1997.

[18] P. Gang, H. Xinhan, G. Jian, and L. Cheng , "Camera modeling and distortion calibration for mobile robot vision," Proceedings of the 7th World Congress on Intelligent Control and Automation (WCICA), pp. 1657-1662, WCICA'08, 2008.

[19] F. Bonin-Font, A. Ortiz, G. Oliver, "Visual Navigation for Mobile Robots: A Survey", Journal of Intell Robot System, 53:263–296, DOI 10.1007/s10846-008-9235-4, 2008.

[20] K. Atsushi, U. Ryo, I. Toshiyuki, T. Teppei, S. Takeaki, D. Jun, K. Mitsumasa, and U. Masaru, "Development of a high speed vision system for mobile robots," IEEE International Conference Intelligent Robots & Systems, pp. 1372-1377, IROS, 2006.

[21] B. Abdul, S. Robert, K. Yahya, And M Gloom, "A hybrid approach towards vision based self-localization of autonomous mobile robots," Proceedings of the International Conference on Machine Vision, ICMV-2007, pp. 1-6, 2007.

[22] L. Ho-Dong, K. Dongwon, P. Min-Chul, and P. Gwi-Tae, “Augmented reality based vision system for network based mobile robot,” Proceedings of the Computer-Human Interaction - 8th Asia-Pacific Conference, APCHI 2008 vol. 5068 LNCS, pp. 123-130, 2008.

[23] D. Filliata and J. Meyer, “Map-based navigation in mobile robots: I. A review of localization strategies,” Cognitive Systems Research, 4, 243–282, 2003.

[24] R. Araujo, "Prune-Able Fuzzy ART Neural Architecture for Robot Map Learning and Navigation in Dynamic Environments", IEEE TRANSACTIONS ON NEURAL NETWORKS, vol. 17, no. 4, 2006.

[25] S. Tomohiro, M. Yoshio, K. Taichi, I. Masayuki, and I. Hirochika, “Development and integration of generic components for a teachable vision-based mobile robot,” IEEE/ASME Transactions on Mechatronics, vol. 1, no. 3, pp. 230-236, 1996.

[26] M. Ryosuke, T. Fumiaki, and M. Fumio , “Skill acquisition of a ball lifting task using a mobile robot with a monocular vision system,” IEEE International Conference on Intelligent Robots and Systems, pp. 5141-5146, 2006.

[27] N. Vlassis, G. Papakonstantinou, and P. Tsanakas, “Robot Map Building by Kohonen’s Self-Organizing Neural Networks,” Proceedings of 1st Mobinet Symposium, Athens, Greece, 1997.

[28] P. Changhan, K. Sooin, and P. Joonki, “Stereo vision-based autonomous mobile robot,” Proceedings of SPIE - The International Society for Optical Engineering, vol. 6/6, Intelligent Robots and Computer Vision XXIII: Algorithms, Techniques, and Active Vision, 2005.

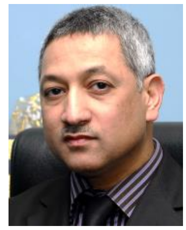
[29] S. Thrun, “Learning metric-topological maps for indoor mobile robot navigation”, Artificial Intelligence Journal, vol. 99, pp. 21-71, 1998.

[30] F. Nima, T. Mohammad, and S. Sadaf, “Intelligent real time control of mobile robot based on image processing,” Pro of IEEE Intelligent Vehicles Symposium, pp. 410-415, vol. IV, 2007.

[31] D. Murray and L. James, “Using Real-Time Stereo Vision for Mobile Robot Navigation,” Journal of Autonomous Robots, 8, 2000, pp. 161–171.

[32] D. Guilherme and K. Avinash, “Vision for Mobile Robot Navigation: A Survey,” IEEE Transactions on Pattern Analysis and Machine Intelligence, 24, 2, 2002, pp. 237-266.

[33] K. Al-Mutib, E. Mattar, M. Alsulaiman, and H. Ramdane, “Stereo Vision SLAM Based Indoor Autonomous Mobile Robot Navigation”, IEEE ROBIO-2014, International Conference on Robotics and Biomimetics, Dec 2014, Indonesia.



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