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Noble Approach on Sensor Fused Bio Intelligent Path Optimisation and Single Stage Obstacle Recognition in Customized Mobile Agent

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Abstract

Optimized PTP (Point to Point) Navigation by customized mobile agent constitutes extensive research domain in Machine Intelligence. Distinct Literature survey confirms the proposal of SLAM (Simultaneous Localization And Mapping) mediated sensor usage for visual data collection in a particular GPS (Global Positioning System) - denied indoor environment. This has been further followed by fused data collection using multi sensor for obtaining long time and high precision localization and obstacle detection in MRN (Mobile Robot Navigation). This paper proposes an idea to incorporate machine learning module for data modeling so that the obstacle detection and identification results in relatively more precise, accurate and efficient. The comparative numerical analysis has been presented to establish the proposed methodology. Along with this, Fusion SLAM algorithm has been created and proposed which combines features of both 2D LiDAR (Light Detection And Ranging) and RGB-D (Red, Green, Blue Depth) SLAM, resulting in visual reference of combined detected periphery and reconstructed 3D depth of on-path obstacles. The aforesaid procedure is further extended with integration of Bio Intelligent path planning approach. Experimental analysis carried out with sample candidate functions with respect to concerned mobile robot and considered indoor environment has been presented which would prove to be important citation for further research in the domain of collision-free optimum MRN.

Keywords: PTP (Point To Point) Navigation; Machine Intelligence; SLAM (Simultaneous localization And Mapping); GPS-denied; MRN (Mobile Robot Navigation); Fusion SLAM; Bio Intelligent path planning approach.

1. Introduction

AGV (Automated Guided Vehicles) generally equipped with depth sensors are able to perceive the surrounding and executes proper point-to-point navigation[1]. To enhance the performance measure of AGV, the sensors are being fused for combined obtainment of data in coordinate as well as depth format for relatively high precised obstacle detection. In this work, one RP LiDAR (RoboPeak LiDAR) has been preferred over other existing sensors. RP

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LiDAR has the specific capability to scan the environment approximately 12m by radius and it possesses the quality to produce perfect periphery detection of the obstacles. Along with this, Intel Realsense D455 RGB-D (Red Green Blue-Depth) sensor has been taken into consideration for their rigid performance in measurement extraction [3] to produce fusion [2] of 2D as well as 3D depth capture of the object. Primary contributions of this work has been categorized into following parts:

- Creation and usage of a self customized differential drive designed mobile robot platform (CUBot), architectured on differential drive mechanism.
- Fusion of 2D and 3D sensors for proper detection of on-route static and dynamic obstacles with creation and application of Fusion SLAM.
- Integration of Single Stage Object Detector (SSOD), a machine learning approach to make the obstacle recognition more efficient, precise and accurate to obtain optimum navigation with less consumption of time and low release of energy.
- Achievement of optimum point to point path by detecting and avoiding the obstacles on the basis of fused sensor data using Bio Intelligent path plan approach.

Integration of CUBot with fused sensor and Robot Operating System (ROS) [4] make a trace of VI (Visual Inference) serving as a memory so that based on this the robot discard the already explored path and make decisions to traverse the unexplored path in search of optimized trajectory from start to desired goal point [5].

The concerned paper illustrates a specialized technique of optimized path finding decision accompanied with probabilistic prediction and realistic classified object detection and recognition. This paper introduces combination of ML (Machine Learning) module as prime contribution, resulting in better recognition relative to existing procedures. The analysis of existing works and experimentation with SSOD (Single Stage Object Detection) algorithm, YOLO (You Only Look Once) is found to be comparatively better in accuracy for object prediction with better probability with respect to our created constraints. Fig. 1 shows the work flow in geometrical format.

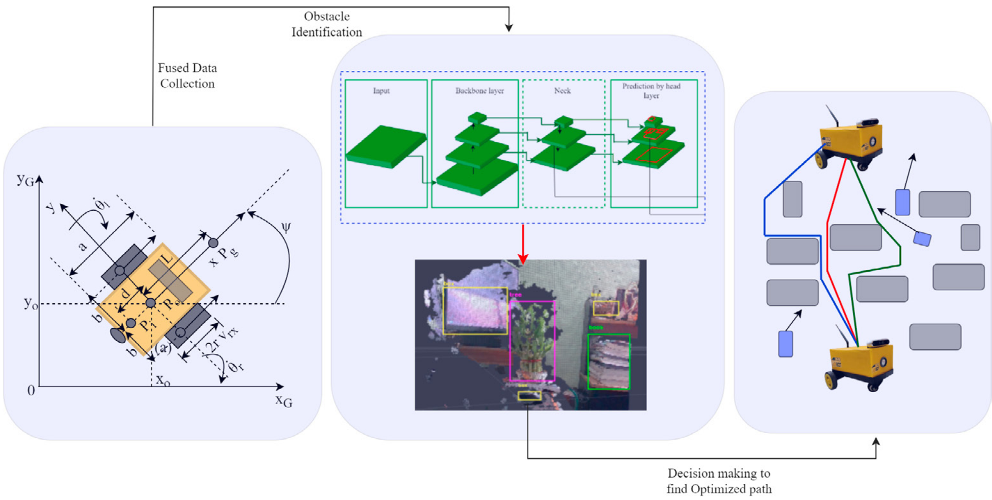


Fig. 1: Model architecture showing the work flow of the concerned work.

Bio inspired approaches prevail as optimization technique working on the natural selection and evolution. Bio intelligent techniques confirms to be comparatively easier and faster and less time consuming in case of real-time scenarios equipped with nonlinear constraints [6]. Besides existing reliable graph theoretic path searching strategies, bio inspired techniques are superseding for having the ability to solve complex-computation problems at a faster rate. BIAS (Bio inspired Intelligent Algorithms) are separated from traditional artificial intelligent method based on their characteristic feature to mimic natural process of individual selection [7]. This acted as the primary motivation to carry out with the special application of this algorithm. Genetic Algorithm, an evolutionary technique, has experimentally proved to be promising performer relative to considered situation. This paper presents analysis of Genetic Algorithm on data obtained from Fused sensor as well as fused data with application of SSOD algorithm based on certain parameters. Subsequent sections present the reviewed works, working architecture of the considered process, algorithmic presentation of the used procedures and lastly verification of the constructed process with valid experimental results.

2. Related Works

Extensive survey and studies are done on Fused sensor data for cooperative near optimum collision free navigation in mobile robots. Performances of various path finding approaches including both Graph theoretic as well as bio inspired are noted.

Zingg et al.[14] presents a remarkable work making video cameras as the main sensor for navigation integrated with suitable on path obstacle detection and avoidance. A combined application of RGB-D camera, is noticed in in paper [15], working by the principle of kinect and an IMU followed by generation of 3D feature points showing visual Odometry with integration of depth information into RGB color information in highly dynamic environments. Labbé et al. [16] proposed first remarkable SLAM method for detection and tracking of moving objects using laser range finder and verified it in outdoor urban environment.Pfrunder et al. [17] used SLAM maps for obtaining occupancy grid having a memory needed for collision-free navigation in heterogeneous environments. [18] proposes and presents online multi-session Graph-based SPLAM (Simultaneous Planning, Localization And Mapping) along with Long-Term memory management. Azartash et al. [19] compute partitioning of RGB-D images for individual estimation of motion of each region for region determination belonging to the moving object. Rapti Chaudhuri et al. presents a keen way for determining and recognizing on path obstacle perfectly on the basis of RGB-D sensor input by scanning the indoor environment in [20]. Alcantarilla et al. [21] introduces a special Visual SLAM system for eliminating associated data accompanied with identification of moving object within a range of about 5 meters and in some non-artificial or low-textured scenes this system sometimes misjudges static points as dynamic ones. In the work of [22] a bio inspired neural-network based approach for solving coverage planning problems applicable for UAV (Unmanned Aerial Vehicle) in case of collision-free traversal of severe areas has been noticed. Bio intelligent path planning based on sparrow search algorithm is illustrated and analysed in [23] for finding high convergent and qualitative optimized route. In [24] a new technique based on plant's phototropism has been proposed which is primarily applicable on 3D space for achieving obstacle-less path traversal in case of UAV. The authors in [25] have proposed Social Spider Optimization (SSO) algorithm, a bio intelligent algorithm for obtaining an improvement in data clustering process with respect to their efficiency and accuracy. In [26] an improvised version of neural network model is studied extensively for achieving collision free path planning by Autonomous Underwater Vehicle (AUV). The work presented in [27] evaluates the creation and working principle of a hybrid path planning algorithm and a bio-inspired control followed by the discussion of applicability of the proposed methods in case of omni wheel mobile robot.

The concerned work distinguishes itself by introducing Fusion SLAM algorithm consisting of the features from both 2D and 3D SLAM. It also combines the Machine Learning Data modelling module for perfect identification and localization of on route obstacles.

3. Methodology

This section provides the basic structural idea of the process flow maintained in this work to obtain the desired output. The subsequent subsections further divides the procedure into certain parts, the role of which are discussed in a brief manner with referential visual as well as algorithmic presentation. The schematic representation in Fig. 2 clarifies the work flow more to be accommodated with.

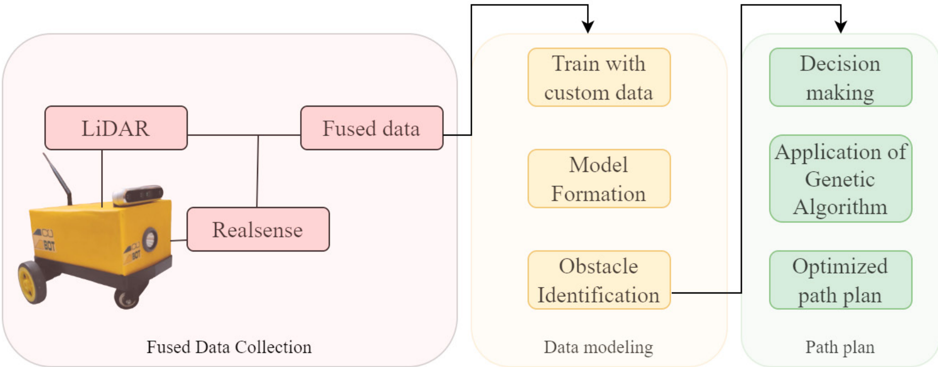


Fig. 2: Model architecture showing the work flow of the concerned work.

3.1. Collection of Fused Data

2D LiDAR has been considered in the concerned work for incorporating the 2D depth data of the on route obstacles. Three variants of 2D LiDAR taken for capturing various data are mentioned below. For collecting 3D depth data of the obstacles Intel Realsense D455 has been preferred over other onboard sensors for getting precise detection of clashing objects. Both the coordinate and depth data achieved respectively are fused together through proper sensor calibration needed for further achievement of optimized point to point collision free Mobile Robot Navigation (MRN) within finite amount of time.

- *RPLiDAR.* This work preferred A1M8 model of 2D RPLiDAR for two dimensional scan of indoor environment [8]. The triangular measurement process allows limited periphery detection of the one plane on path obstacles. Maximum range of scanning is approximately 12m by radius which allows subsequent detection of every possible nearest obstacles at finite amount of time.

- *Intel Realsense D455 RGB-Depth sensor.* 3D depth data measurement is obtained from from Realsense D455 [9]. Physical characteristics of Intel Realsense D455 includes Vision Processor D4, IR projector, RGB colour sensor, IMU and depth module (2HD image sensors).

- *Combined Sensor calibration and obtainment of fused data.* The coordinate data obtained from LiDAR is integrated with the 3D depth data from Realsense D455. The hindrance of 2D LiDAR in scanning the other plane obstacle is covered up with perfection by RGB-D sensor [10]. World coordinate R is forecasted to image coordinate and the representation is shown below in equation (1):

$$R = J(TR + p) \tag{1}$$

where J is 3×3 camera intrinsic parameter, T presents 3×3 camera orientation matrix and p denotes 3×1 vector relative to its position. Equation (2) depicts S_g, the point for presentation of rigid transformation from camera coordinate system to LiDAR coordinate system.

$$S_g = \delta S + \epsilon \tag{2}$$

δ depicts 3×3 camera orientation orthonormal matrix relative to LiDAR and ϵ denotes 3×1 vector relative to its respective location.

3.2. Path plan in indoor environment

In execution of this challenging task of obtaining collision free smooth indoor path navigation, among most of the computational and experimental challenges, environment type constitutes one of the primary aspects to look into. Categorical analysis has been done on problems faced on indoor GPS-denied environment:

- Low light condition - Absence of light or presence of dim light in an indoor environment creates a problem to visualize and decide the optimum path.
- Presence of dynamic Obstacles - Dynamic on- path obstacles create more clashes including run time constraints compared to static obstacles Unstructured and unknown sudden change of object position place the mobile agent in a puzzled situation to make immediate decision [11].
- Reachability - Reachability portrays the access of the constructed algorithm to find the minimum obstacle free path out of many possible trajectories in a congested noisy surrounding [12]. Fig. 3 (a) portrays the different types of indoor environment faced by the mobile robot.

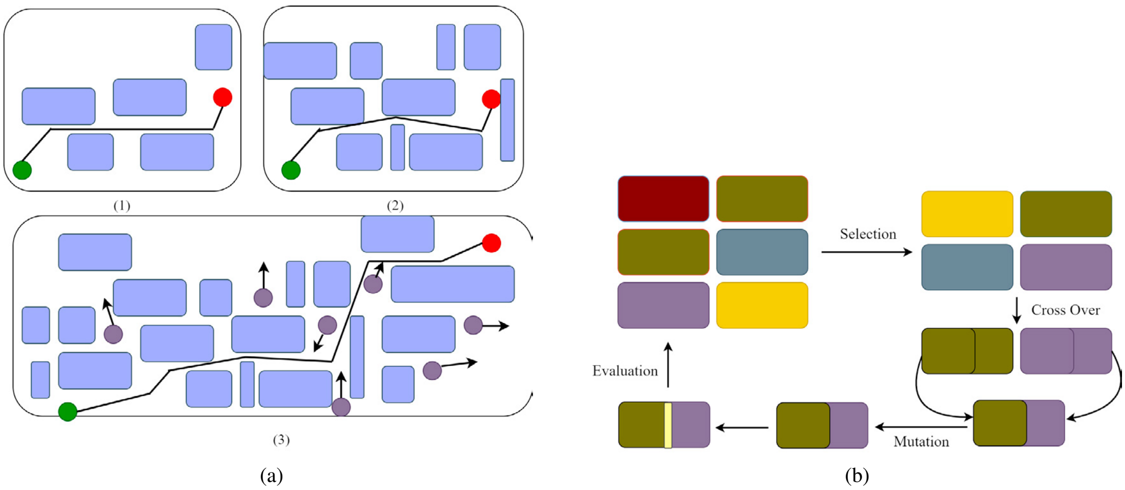


Fig. 3: (a) Types of environment needed to face by mobile robot in obtaining point to point collision free navigation (b) Working procedure of Genetic Algorithm in path planning by customized mobile robot.

3.3. Application of Fusion SLAM

Fusion SLAM has been created and proposed by combination of features of 2D LiDAR as well as RGB-D SLAM (Algorithm 1). Data from both the sensors are taken and fused together to obtain relatively precise and efficient obstacle detection for achieving collision-free path locomotion. Data from two sensors and a priori map are considered as input. As a result, optimum pose estimated graph with occupancy grid map have been formed. Optimal pose estimation of the robot with respect to sensor is obtained by rigid body transformation $(\epsilon) = [Q_x, Q_y, \phi]$ from the robot to the prior map. $M(R_i(\epsilon))$ is the value of the map at $R_i(\epsilon)$, world coordinate of scan end points $R_i = (R_{i,x}, X_{i,y})^T$. $M(R_i(\epsilon))$ obeys the function as mentioned in equation (3).

$$R_i(\epsilon) = \begin{bmatrix} cos\phi & -sin\phi \\ sin\phi & cos\phi \end{bmatrix} \begin{bmatrix} R_{i,x} \\ R_{i,y} \end{bmatrix} + \begin{bmatrix} Q_x \\ Q_y \end{bmatrix} \tag{3}$$

Minimum error is added to the actual pose for achieving final optimized pose estimation.

For normal RGB image, 2D LiDAR SLAM is performed. For depth image, after pairwise 6D transformation estimation 2D pose expression in done followed by 3D point cloud map formation. For accuracy further Optimization of the pose expression is done. Besides, accurate strategic path is also obtained with more probabilistic accurate prediction. The optimized graph is considered as output of Fusion SLAM.

Algorithm 1 Fusion SLAM for mapping the path exploration using fused sensor data input

Input: - $f(sen_1)$, $f(sen_2)$, $map_{a-priori}$ // lidar data, depth data, and a priori map
Output: - ϵ^*,a_c,a_p, Occupancy Grid map // Optimal Pose estimation of the robot

Calculate probability of an absorbed grid.
Divide the grid map.
for $R_i \in map_{a-priori}$ **do**
    $\nabla \mathtt{M}(R_i) = \left(\frac{\delta M}{\delta x}(R_i), \frac{\delta M}{\delta y}(R_i)\right)$
end for
Estimate gradient and derivatives using four closest integer coordinates namely, R_{00}, R_{01}, R_{10} and R_{11}.
$M(R_i) \approx \frac{y-y_0}{y_1-y_0}\left(\frac{x-x_0}{x_1-x_0}M(R_{11}) - \frac{x_1-x}{x_1-x_0}M(R_{01})\right)$
$+\frac{y1-y}{y1-y0}\left(\frac{x-x_0}{x_1-x_0}M(R_{10}) - \frac{x1-x}{x1-x0}M(R_{10})\right.$
$\left.-\frac{x1-x}{x1-x0}M(R_{00})\right)$
$\frac{\partial M}{\partial x}(R_i) \approx \frac{y-y_0}{y_1-y_0}M\Big((R_{11}) - M(R_{01})\Big)$
$+\frac{y_1-y}{y_1-y_0}M\Big((R_{10}) - M(R_{00})\Big)$
$\frac{\partial M}{\partial y}(R_i) \approx \frac{x-x_0}{x_1-x_0}M\Big((R_{11}) - M(R_{10})\Big)$
$+\frac{x_1-x}{x_1-x_0}M\Big((R_{01}) - M(R_{00})\Big)$
Estimated pose computed and expressed in 2D environment.
for `RGB image, Depth Image` **do**
    Pairwise 6D Transformation Estimation performed by RANSAC
end for
Pose expression in 2D Environment. $\in= (R_x, R_y, \chi)^T$.
Global Pose Graph Optimization (g^2o)
3D point clouds formation
Optimize the pose expression by matching the laser data and the map.
for $\in= (Rx, Ry, \chi)^T, map_{output} \leftarrow M(Rj(\in))$ at $Ri(\in)$ **do**
    $\in^*= \arg\min_{\in} \sum_{i=1}^{N}[1 - M(Rj(\in))]^2$
    for $\epsilon \leftarrow \epsilon + \Delta\epsilon$ **do**
        $\sum_{j=1}^{N}[1 - M(Rj(\epsilon))]^2 \rightarrow 0$
    end for
end for
Accuracy in obstacle detection (a_c)
Accurate explored path (a_p)
$\in^* \leftarrow \in$

3.4. Application of SSOD to recognize obstacles

Primarily, the idea of performance measure obtained from YOLO v3 and YOLO v4 has been incorporated as SSOD in this work. Literature review and experimental outcome confirms YOLOv4 model to serve more advantages in terms of optimal speed and detection accuracy. The YOLO model make usage of a one step framework upon global context, mapping directly from image pixels to bounding box coordinates and category probabilities. The YOLOv4 architecture consists of four distinct blocks namely backbone, neck, dense prediction and sparse prediction. The backbone is characterised primarily for feature extraction. The neck comprising of a number of bottom-up and top-down paths, is used for collecting feature maps from different stages. The last detection is done by using Head block of the architectural model.

For object detection, it dependes on the count on the probability of presence of detected bounding box in the grid cell. In a specific cell, (x,y) denotes the center of the bounding box, (w,h) depicts the widths and heights of the detected object that are normalized with respect to the image dimensions , and C denotes the confidence score. Final detection is done based on all these parameters. Rounding off each detection includes certain important factors like objectness score computation, boundary box regression, and classification score.

3.5. Application of Bio Intelligent Approach for path planning

Genetic Algorithm (GA) is an evolutionary heuristic search technique based on natural theory of Darwin. It works on the primary principle of adaptation of group of animals to the environment. Subsequent parts in evolution involves selection, reproduction, crossover and finally mutation as portrayed in Fig. 3 (b).

Genetic Algorithm (GA) also follows the same procedure to find global minimum solution. Each chromosome of an individual acts as the possible path to be traversed. After multiple steps of exploration, evaluation and integration the final chromosome giving the best resultant is considered as optimized path [13]. The stochastic optimization algorithm is mentioned in Algorithm 2 with input, entire working process and resultant output. Fitness (f) of a chromosome (M_x, N_x, M_y, N_y) is calculated by the formula presented in equation (4).

$$f = \frac{1}{d(M_x, N_x) and (M_y, N_y) + d(M_y, N_y) and (M_g, N_g)} \tag{4}$$

'y' belongs to generated chromosome after crossover and 'g' is the target chromosome. 'd' presents the distance between the respective chromosomes. Algorithm 2 presents the Genetic algorithm working procedure.

Algorithm 2 Genetic Algorithm for finding optimum path

Input: *population*, *target[m]*, *chromosome[m]*, *fitness*, *output[m]*
Output: *new_y*

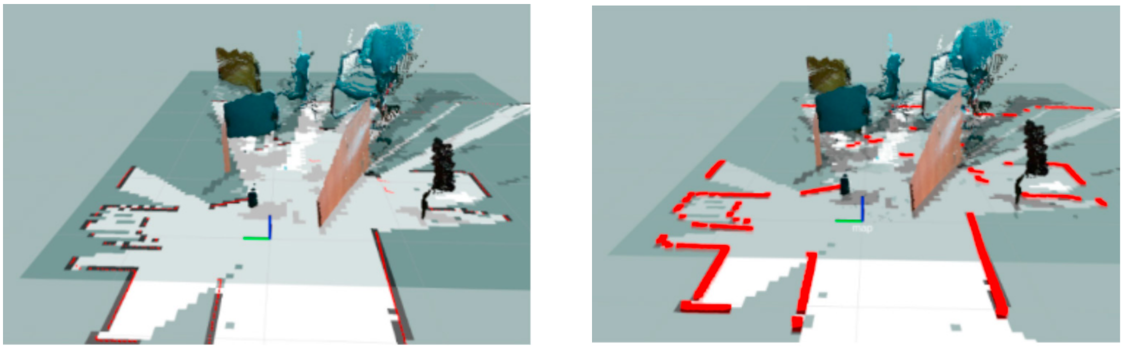
```
y = population;
fitness = 0;
for m in range y do
    if chromosome[m] ≠ target[m] then
        fitness = fitness + 1;
        return fitness;
    end if
end for
if output[m] < target[m] then
    for m in range y do
        parents[m] = y[m];
        Compute crossover result and put in variable crossed_y
        new_y = crossed_y;
        repeat step 3
    end for
end if
return new_y
```

4. Experimental Analysis and Results

This section depicts the experimental and numerical analysis with brief explanation of each part in subsequent sections. Results obtained from Fusion SLAM followed by detection and exploration of path.

4.1. Fusion SLAM results

Combined Periphery of the obstacles and the explored path by the customized mobile robot as well as the respective 3D voxel network of explored surroundings is obtained by applying Fusion SLAM. The virtual 3D reconstruction is created in Rviz visualizer of ROS (Robot Operating System) with the help of dense point cloud. Fusion SLAM is performed and the periphery of the obstacles are detected and marked in red. Comparative study of individual sensor data and fused sensor data have been introduced in tabular format. The undetected obstacles by LiDAR has been correctly identified by fused sensors and the trajectory is obtained perfectly during the traversal. The experimental results depicted in Fig. 4 gives the visual reference of result obtained by application of Fusion SLAM.



(a) (b)

Fig. 4: Results obtained after applying Fusion SLAM depicting both periphery detection of obstacle and 3D reconstruction of environment.

4.2. Accuracy of Fusion SLAM with SSOD

Experimental procedure has been carried out by taking 20 on-path obstacles and the obtained results are analysed numerically and presented in Table 1.

Table 1: Experimental comparison of various SLAM mediated strategic procedures.

Sensor used	Data obtained	Obstacles present	Obstacles Detected	Accuracy
2D LiDAR	range, intensity, angle, time increment	30	27	90%
3D RGB-Depth sensor	RGB, depth, accelerometer and gyro data	30	26	86.6%
Fused Multi sensor	coordinate and 3D depth data	30	28	93.3%
Fused sensor with SSOD	coordinate and depth data with recognized obstacle in bounding box	30	**29**	**96.6%**

4.3. Results of bio intelligent approach on sample candidate function

Genetic algorithm is analysed on the basis of certain parameters like the optimized variable taken through a specific fitness function provided, number of iterations, and the best value of the objective function (f) extracted after optimization. Genetic Algorithm has been applied on input obtained from Fused sensor data as well as Fused sensor data with SSOD. It is applied on three specific fitness function with respect to the area covered by the mobile robot in the considered environment and the results are presented on experimental Table 2.

Table 2: Experimental table presenting comparison between the performance of respective algorithms.

sample candidate function	algorithm	x_{value}	y_{value}	optimized value of f
f = 3x + 5y	GA with Fusion SLAM and SSOD	**-846.3**	**-1107.7**	**-8077.1**
	GA with Fusion SLAM	-870	-1078	-8000
f = x^2-7y^2	GA with Fusion SLAM and SSOD	**-3**	**1366.8**	**-1.3077e+07**
	GA with Fusion SLAM	-1.987	1059	-1.1214e+07
f = (x^2-4y) - (8-7x)	GA with Fusion SLAM and SSOD	**-2.7**	**1064.6**	**-4278.0**
	GA with Fusion SLAM	-1.8	964	-3873.36

Conclusion

This paper proposes combined working model of machine learning approach of obstacle detection strategy accompanied with Fusion SLAM algorithm followed by application of Genetic Algorithm for obtaining optimum Point To Point Navigation. The experiment is carried out in sampling area simultaneously using both the sensor data and construction of Fusion SLAM for visual reference to take further decision by the mobile robot. Comparative study of performance obtained by individual sensor and fused sensor clarifies the perfectness of our proposed method numerically. Experimental results presented in tabular format using sample candidate function with respect to taken indoor environment and customized mobile robot platform clarifies the performance measure of Genetic algorithm to be better in case of proposed method compared to other. The presented resultant data could be cited for future research in the domain of Fusion SLAM mediated smoothly planned point-to-point navigation through precise object identification by SSOD.

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