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Sparsed Potential-PCNN for Real Time Path Planning and Indoor Navigation Scheme for Mobile Robots

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***Abstract* - One of the main problems associated with mobile intelligent agents is path planning. Numerous approaches have been presented for path planning of mobile robots. One of the most efficient methods is Pulse Coupled Neural Network (PCNN). This paper presents a novel approach we call the Sparsed Potential PCNN method for real time path planning for mobile robots. In the proposed method a Potential Field approach is used to limit the propagation of the autowave only in the direction of the destination rather than propagating in all directions. This increases the efficiency of the PCNN algorithm. Furthermore a sparsing technique is applied to make the algorithm even more time efficient. The algorithm has proven to be a robust and time efficient path planning scheme. The Sparsed Potential-PCNN plans the shortest path in the shortest possible time. The algorithm is also capable of avoiding obstacles in its path. Simulation results in Player/Stage for Pioneer 3 AT mobile robot navigating among obstacles in an indoor environment are also presented to demonstrate the effectiveness of the proposed algorithm.**

Index Terms -Path planning, Pulse-coupled neural networks (PCNNs), Potential field method, Sparsing, Mobile robot navigation.

I. INTRODUCTION

The determination of the shortest path from the starting point to the finishing point is a common problem in robotics. For mobile robots this needs to be done in real time which becomes a challenge for large maps with complex environment as path planning is computationally very expensive. Several methods have been proposed to solve the path planning problem. There are some global methods such as road map [1], cell decomposition [2,3] and distance transform [4] which were able to search for possible paths in the whole workspace. These methods are mainly suitable to static environments, and are computationally expensive in complex environments. Another category of local methods, such as potential field method [5-10] and the grid-based algorithms [11-12], have been proposed to provide effective path searching. However, majority of these methods suffer from undesired local minima.

Recently researchers have developed new methods that include fluid model [13], dynamic wave expansion model [14] and neural networks [15-19]. The techniques developed using neural networks that can be used for path planning include Self Organizing map(SOM) based model [20-21], Grossberg's shunting model [22], cooperative extended Kohonen maps (EKMs) [23] and Pulse Coupled Neural Network(PCNN) [24-25].

A Pulse-Coupled Neural Network (PCNN) is a biologically plausible computational algorithm, which is similar to the Locally Excitatory Globally Inhibitory Oscillator Network (LEGION) model [26] for real-time image segmentation, figure/ground segregation, and many other applications. Recent research shows that the spatio–temporal dynamics of PCNNs provide good computational capability for solving a number of optimization problems.

In 1999, the idea of utilizing the autowave in PCNNs was presented in [25], the autowave was used to find the solution to the maze problem in [24]. The model presented in these papers can find the shortest path quickly with minimum effort, where the solution is related to the length of the shortest path and independent to the path graph complexity. However, many neurons are needed to find the shortest path in large mazes or graphs. This is due to the fact that one pulse of the coupled neuron corresponds to a unit length of path. A Modified PCNN (MPCNN) was later introduced by [24] which works in dynamic environments and does not depend upon prior knowledge of target or barrier movements. This MPCNN model uses autowaves for path search. It searches for the shortest path in all directions by continuous time based firing of neurons. The target neuron fires first, and then the firing event spreads out, through the lateral connections among the neurons, like the propagation of a wave. Obstacles have no connections to their neighbors. MPCNN takes fewer neurons to compute the path than classical PCNN. Though MPCNN claims to find the shortest path in shortest possible time but it still is inefficient for online path planning of mobile robots because of its uninformed search behavior.

The Potential Field Method (PFM) has been used extensively for path planning and obstacle avoidance because of their simplicity and time efficiency. PFM utilizes virtual force fields for the determination of obstacle free path. However PFM has significant problems inherent in its model [29]. MPCNN discussed above is free of these problems. In order to overcome the shortcomings of PFM and improve the time efficiency of MPCNN, in this paper we propose a novel combination of these two approaches in order to carry out real-time collision-free mobile robot-path-planning. We term the novel method as Sparse Potential based PCNN. The fundamental idea behind the proposed approach is to create a biased autowave in the direction of robot during path planning.

The proposed model is topologically organized with only local lateral connections among neurons. It needs very few neurons, since the pulse propagation does not correspond to a unit length of path. Instead, the generated spiking wave in the proposed network spreads at a constant speed so that the time of travel between two neurons is proportional to the path length between them so the computational complexity of the algorithm is only related to the length of the shortest path and is independent of the workspace complexity and the number of existing paths in the map. Each neuron in the proposed model propagates a firing event to its neighboring neuron without any comparison computations. The proposed model also works in real time and requires no prior knowledge of target or barrier movement, no explicit optimization of any cost functions, and no explicit searching over the free workspace or collision paths. It is, therefore, useful for real-time robot path planning of mobile robots without the need of any prior learning procedures. By using Potential based PCNN, path-planning becomes so fast it can not only be done in real time but it can also be used as a threaded module in a behavior-based mobile robot. It is computationally less expensive and the path search area becomes much smaller.

Control strategy developed for robot navigation involves determining the pose of the robot between all consecutive neurons. This present pose is maintained until the robot achieves that neuron. At that point the pose for the next neuron is selected and the robot continues is motion. This strategy ensures a smooth collision free movement of the robot. The paper also includes Player Stage [27] simulation results of Pioneer 3-AT mobile robot navigating in an indoor environment.

The remainder of this paper is organized as follows. In section II the existing MPCNN method is discussed. In section III we present the sparsed potential based PCNN. Section IV discusses the navigation and control architecture. Section V comprises simulation results of mobile robot navigation in a SLAM based environment map using our approach. Conclusions and future work are presented in Section VI.

II. Existing PCNN Approach

Recently proposed PCNN algorithm for mobile robot path planning is studied. In this algorithm all the pixels in the 2D map of the environment are considered as neurons and the current robot position and target location are identified. The search proceeds in the form of a pulse through which neighboring neurons are coupled. When the internal activity of a particular neuron exceeds the threshold level, it fires. Initially the target neuron's internal activity is set greater than the threshold level to start the firing process. The fired neuron prepares its neighbors to fire at a later time thus becoming their parent. Subsequently the internal activity of the neighboring neurons increases with time. This firing pattern propagates outwards in the form of a wave until the robot neuron is reached. In this process, internal activity of the obstacle neurons is kept zero, hence avoiding their firing. Path is traced backwards from robot to target through a sequence of parents of the neuron.

The algorithm searches for the robot neuron in all directions which is an unnecessary overhead. Our method seeks to eliminate this by intelligently searching in the direction of the robot neuron.

III. Sparse Potential Field based PCNN

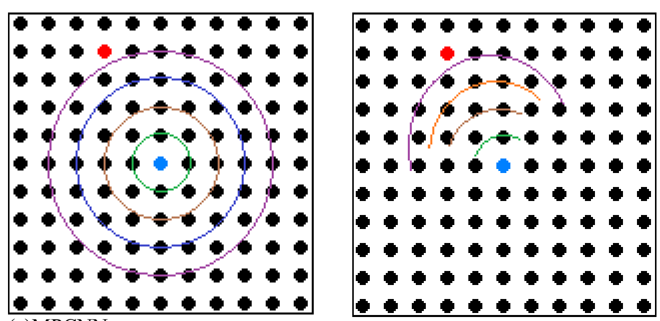
This section demonstrates our approach. Features of the proposed scheme include potential field based approach for implementation of PCNN and increasing the time efficiency of the PCNN nine times through sparsed representation of the environment map. The proposed method is thoroughly tested in PlayerStage simulations.

A. Potential Based PCNN

The central idea behind the Potential based PCNN is the introduction of a potential field into the MPCNN algorithm in order to direct its autowaves towards the robot neuron. PFM consists of two fields, the attractive and the repulsive fields. Attractive field is a measure of distance of a certain neuron to the robot neuron and repulsive field provides the effect of obstacle avoidance in a way that it represents the distance of a certain neuron to the nearest obstacle. As the autowave can be biased towards the robot neuron with only an attractive field thus the repulsive field is neglected as an unnecessary overhead. Attractive field is calculated as below.

$$P = \frac{1}{2}kd^2 \qquad (1)$$

Where d Euclidian distance of present neuron location to the robot neuron and k is a constant.



(a)MPCNN (b)Potential PCNN

Fig. 1. Wave Propagation in MPCNN and the proposed Potential-PCNN.

Since propagation of autowaves in PCNN is time dependent so potential calculated can be devised to generate a time delay in the firing of neurons that are not in the space between the target and robot neurons. Fig. 1 shows the autowave pattern of the original and proposed PCNN scheme. In Fig. 1 robot is shown in red and goal location in blue. The original MPCNN internal activity equation presented in [24] is modified so as to produce a shift in the exponential function. The proposed internal activity of neurons is given as

$$U(t) = \frac{Cw_{ij}}{B}\left(1 - e^{\frac{B}{w_{ij}}[(t_p - t) - P]}\right) \qquad (2)$$

Where:

$U(t)$ = Internal activity of a neuron at time‘t’.

C = A positive scalar constant.

w_{ij} = The connection weight from i to j.

B = A positive scalar constant.

t_p = Parent fire time.

t = Current network time.

P = Potential of neuron i.

B. *Impact of Sparsing*

Second modification suggested in this paper is the *sparsing* of environment map for path planning. Sparse based environmental model not only improves the path calculation time but also the path dynamics where a smoother track is generated. To create a sparse PCNN map of the environment, the whole map is converted to kernels of size 3x3. As an example one such kernel is shown in the Fig. 2. Then each 3x3 kernel of neurons is analyzed. If the kernel has any occupied pixel a single neuron representing the kernel is designated as an obstacle and otherwise as a free space neuron. If a narrow path exits between two occupied pixels then the neurons represent the original pixels. The sparse representation causes a nine times decrease in the size of map which highly affects the computational and memory efficiency of the algorithm. Sparsing also removes discontinuities in the generated path which makes it easier for a mobile robot to follow.

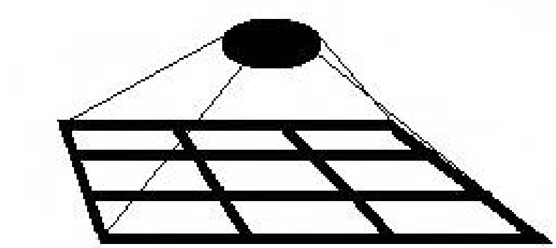
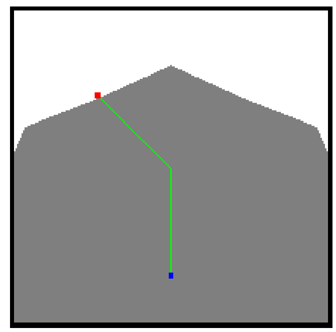


Fig. 2. Sparsing Technique

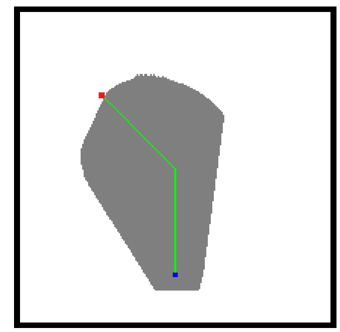
C. *Performance Comparison with MPCNN*

We extensively tested our approach with the MPCNN and found it to be extremely efficient as compared to MPCNN. This time efficiency is due to the directional effect induced into the conventional method by the introduction of potential field. Its time efficiency is further enhanced by sparsing of the environment model.

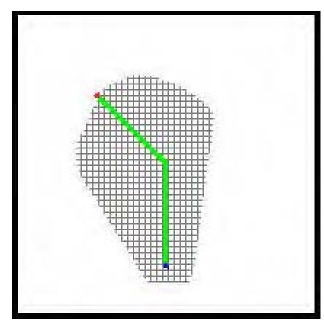
Fig. 3(a) shows the wave propagation in MPCNN. As clear from the figure, the wave propagates uniformly in all directions. Propagated wave of the Potential based PCNN is shown in Fig. 3(b). As clearly evident from the colored space the autowave expands only in the direction of the robot. This demonstrates the effect of PFM in decreasing the effective search space and hence the computation time of PCNN. Sparse results in Fig. 3(c) are presented which shows neurons in the space separated by some distance. In this case results remain the same whereas the computational time further decreases. Robot, path and destination are represented in red, green and blue colors respectively. From Fig. 3 it may seem like there is a straight path between these two points but actually no such path exists because of the small neuron density.



(a)Search Space of MPCNN



(b)Search Space of Potential-PCNN



(c)Result after Sparsing

Fig. 3. Comparison of Search Spaces of MPCNN and potential-PCNN

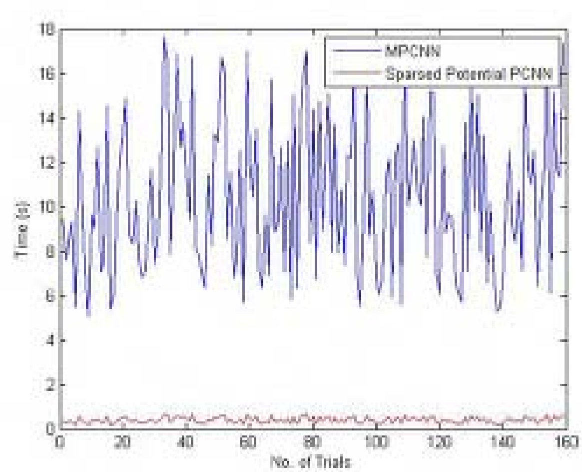


Fig. 4. Time comparison of MPANN with Sparsed Patential PCNN

In order to rigorously check our approach we tested it on 160 different path planning problems. Although the path generated by Sparsed Potential PCNN is the same as path generated by

MPCNN yet the time taken by our approach is considerably less. A clear improvement in the time efficiency is evident in all the results.

IV. Navigation and Control Architecture

For applying the proposed path planning scheme to mobile robot navigation in SLAM environment the proposed navigation and control architecture consists of five major steps which include preliminary localization of the robot in the known map, applying Minkowski sum [28] to get the configuration space, global path estimation and finally generating the control commands to achieve the target location. The complete navigation and control architecture is shown in Fig. 5.

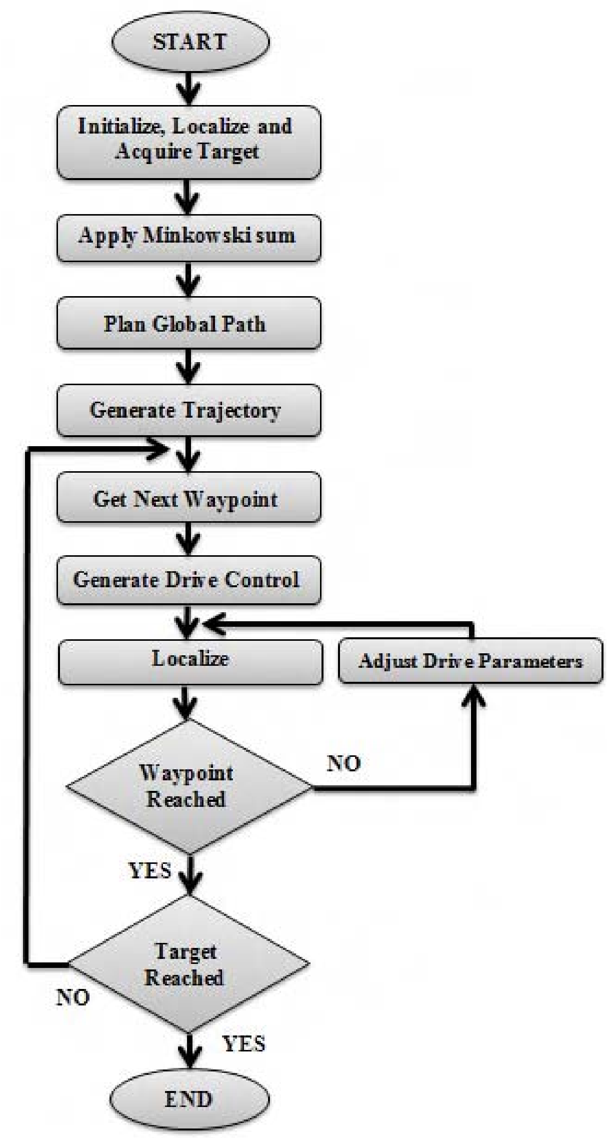


Fig. 5. Navigation and Control Architecture

A. *Localization*

As a first step localization of the robot in the known map is carried out and then target is acquired through online input. Localization is done using odometry data to constantly check the location of the robot. The odometry information was assumed to be without errors in the simulation.

B. *Minkowski Sum*

In order to avoid collision with obstacles, robot's planned path must be suitably away from obstacles. It can be achieved by obtaining the Minkowski sum of the environment map. For the purpose of computational simplicity of the Minkowski sum, the robot was assumed to be circular.

C. *Path Planning By Sparse Potential-PCNN*

The proposed PCNN approach is then applied for global path planning. The algorithm is given the configuration space map. The path planner then estimates the shortest path and returns a series of waypoints in the world coordinates of the environment.

D. *Trajectory Generation*

Since PCNN goes for the shortest path, the returned track has many sharp turns and corners. These sharp turns and corners represent discontinuities that are unachievable by the robot because of its dynamics. Sparsing helps to remove these discontinuities to some extent. Furthermore, parabolic curve fitting was used at the corner points to achieve a smoother trajectory.

Least square method is used to solve the parabolic cure fitting problem. At each corner point, two extra waypoints are generated from the parabolic curve to achieve the purpose of smoothing the planned path. The curve fitting model used is given as

$$P(x) = b_0 + b_1 x + b_2 x^2 \qquad (3)$$

E. *Drive Control*

Waypoints are accessed sequentially by the control program. For each waypoint a drive control is generated. Based upon the Euclidean distance of the robot from the next waypoint, speed and turn rate of the robot is updated. Now the speed and turn rate of the robot is continuously adjusted using the updated localization information until the next waypoint is reached. New control strategy is generated for the next waypoint. This process is continued until the target is reached.

V. Results

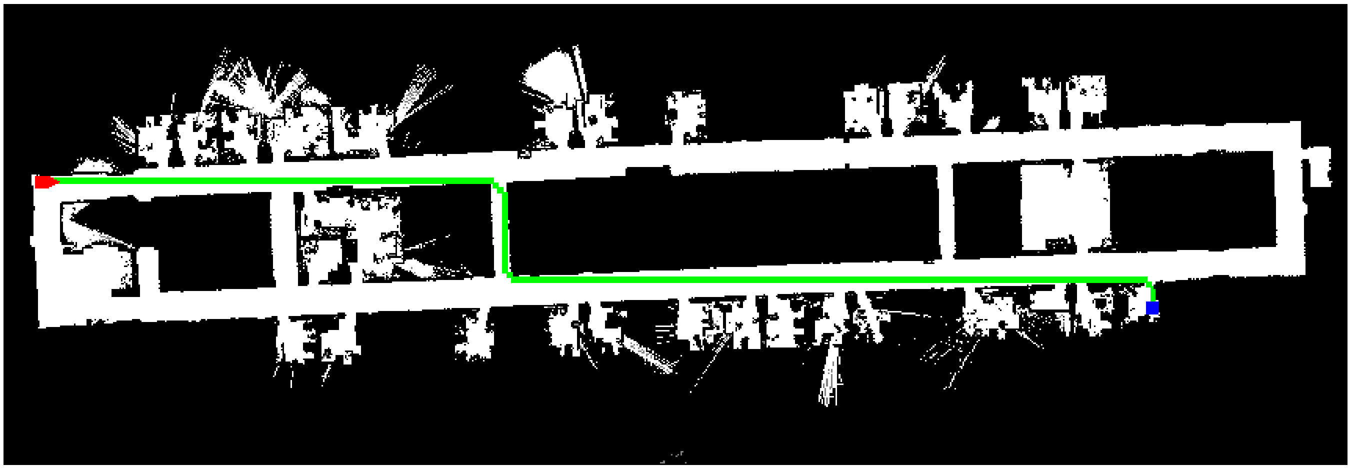
Extensive simulations were performed for the verification of the proposed improvement. The proposed method was tested on an Intel I3 processor with 4GB RAM. For testing of the algorithm we used Player/Stage sample SLAM maps as well as SLAM maps of our own department buildings. The results verify the proposed work.

Fig. 6(a) shows the result of path determined by MPCNN. Fig. 6(b) demonstrates the output from sparse potential-PCNN with parabolic curve fitting to remove discontinuities at corners. Straight path is represented in green color, smoothed path by violet, robot is represented by red and blue represents the destination. Note that the path calculated in the figures does not seem straight that is because the maps based on SLAM do not exhibit a perfectly *square* geometry.

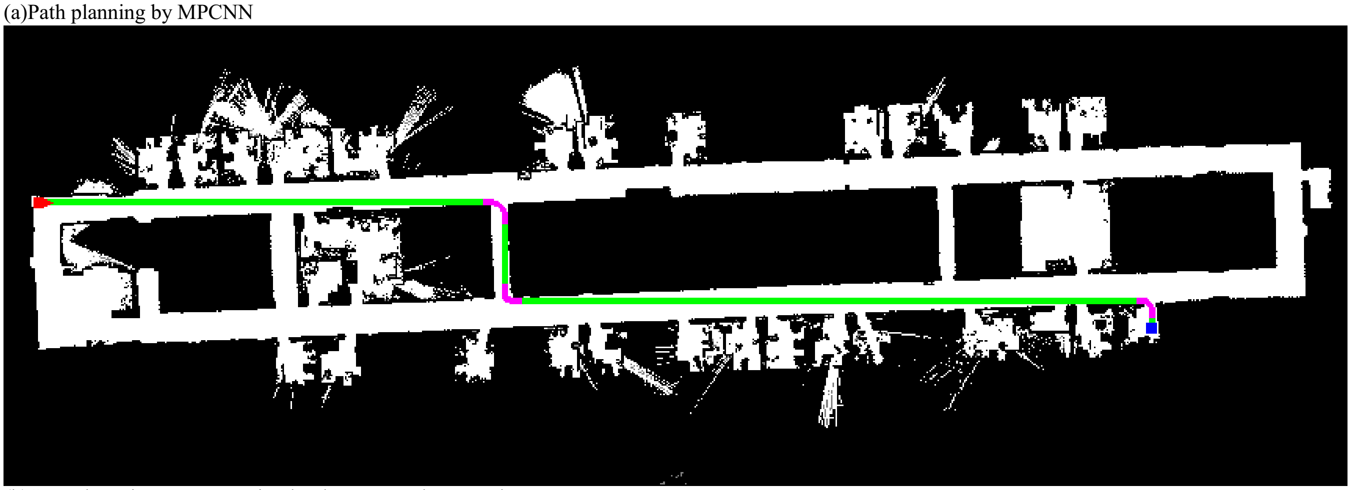
That is why the hallway in the maps is not perfectly horizontal but tilted a little to one side which makes the path, which is otherwise straight, look a little slanted. Fig. 6(c) demonstrates the path followed by the robot in simulation as done in PlayerStage. Fig. 7 represents the result of path planning through proposed method. It is evident from the figures that the reported path is the shortest possible path with smooth turns at the corners.

VI. Conclusion and Future Work

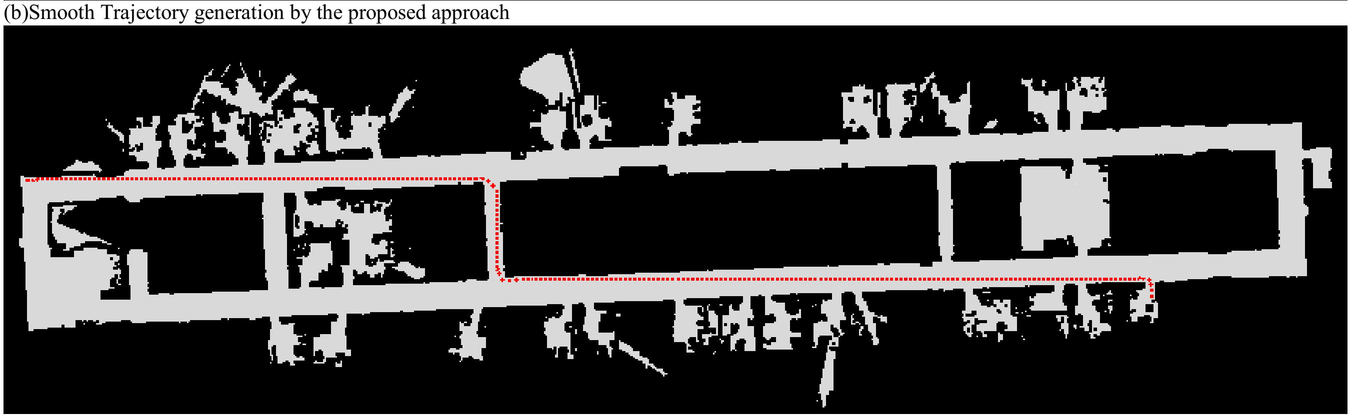
An improved Sparsed Potential-PCNN is presented for path planning of mobile robots indoor environments. The proposed approach decreases computational complexity of MPCNN by limiting the autowave in the direction of robot.



(a)Path planning by MPCNN



(b)Smooth Trajectory generation by the proposed approach



(c)Player/Stage Simulation Result

Fig. 6. Comparison of MPCNN with the proposed method and simulation result.

Effective use of Potential Field method and Sparsing technique has resulted in an increased time efficiency of the algorithm by decreasing the computational area of the environment map. Simulated results of the P3-AT mobile robot navigation in a SLAM environment using the Player/Stage module verify the effectiveness of the new approach.

We are in the process of implementing the scheme on our university's Intelligent Driving System (IDRIS) which is an autonomous research robot for indoor and outdoor navigation. Moreover, we plan to test the algorithm in dynamic environments and with actual sensor noise as well. This work will be a part of our future publications.

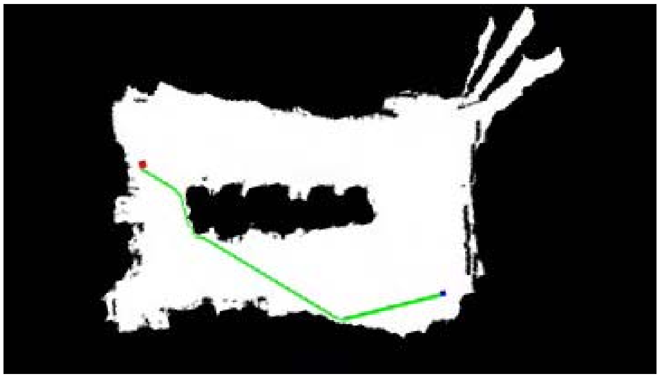


Fig. 7. Proposed method on a Real SLAM environment

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