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**Obstacle Avoidance Challenge**

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# **Introduction**

The obstacle avoidance challenge objective is to produce a fully autonomous robot capable of navigating an area while avoiding collision with objects including other moving robots. The competition will consist of three trials. Each trial will last 12 minutes and have a unique configuration of the competition area. The robots are required to be fully autonomous with no human interference other than the initiation of the program allowed. Any robot that remains stationary for an extended period of time or is only performing repetitive motions will be removed from competition. The scoring will be dependent on distance traversed by the robot and collision avoidance. The challenge demands the application of knowledge learned in and out of the Mobile Robotics class to develop solutions to a practical robotics problem. The intention of the pre-proposal is to provide a comprehensive approach consisting of desirable robotics avoidance techniques based on a review of literature.

# **Literature Review**

The Vector Field Histogram (VFH) method is a real-time obstacle avoidance method for mobile robots. This method creates a two-dimensional Cartesian histogram grid as a world model. This particular method depends on the model to use ultrasonic range finders to continuously update the world model. The VFH is comprised of a two-stage data reduction process that is responsible for the robots control commands. The first stage reduces the histogram grid to a one-dimensional polar histogram that is constructed of the robot’s immediate surroundings. The sectors in the polar histogram contain values that represent polar obstacle density in that particular direction. The second stage identifies the sector with the lowest polar obstacle density and aligns the robot with that direction [1].

Improvements were made with respect to the VFH method to eliminate imperfections. An improved method is referred to as the Enhanced Vector Field Method (VFH+). This enhanced method takes into consideration the width of the robot while the original method used low-pass filter to compensate for the width. The difficulty associated with accurately tuning the low-pass filter enabled the robot to cut corners; therefore, the enhanced method eliminates that difficulty [2]. VFH+ method also considers robot trajectory, uses a threshold partition that results in a reduction of an oscillatory trajectory, and, due to a cost function, can commit to a direction. However, the VFH+ was also deemed to obtain some shortcomings. In particular, VFH+ method and previous methods relied on certainty grids which performed well with ultrasonic sensor, but are not ideal for laser radar. Furthermore, the real-time velocity was not considered which can affect the accurate choice to make in terms of direction. Also, the threshold does not take into consideration influences caused by distribution angles, which if are too high can result in a slowly reacting algorithm or if too low could cause a collision. Finally, the VFH+ requires eight parameters to operate effectively. Those eight parameters can be difficult to be in harmony [5].

Another enhanced method of VFH called VFH\* was designed as a purely local obstacle avoidance method that deals with problematic situations for the original Vector Field Histogram method. The VFH\* is a combination of the VFH+ and the A\* search algorithm. This particular method often overcomes issues with the VFH+ method by evaluating trajectories and their consequences several steps ahead of the current position. The initial VFH+, as stated previously, formulates a histogram and searches for openings and then determines its future direction by assigning a cost value to the possible directions and then chooses the direction with the lowest cost value. However, the VFH\* evaluates the consequences of driving towards each potential direction, or a primary candidate direction, before making a final choice. The VFH\* computes the potential new position and orientation for every primary candidate direction. At each potential projected position the VFH+ creates a polar histogram, and the histogram is evaluated for candidate directions. This process is repeated a predetermined number of times to build a search tree that assists in the robot making the more optimal decision in situations that otherwise would result in an undesirable circumstance. However, the advantage of this method, making the decision that results in a successful traverse, comes at the expense of computational time [6].

The predecessor to the VFH were Potential Fields Methods (PFM) namely the Virtual Force Field (VFF) method that was created by Yoram Koren and Johann Borenstein deals with obstacle avoidance for fast moving mobile robots. The VFF method is a combination of certainty grids and PFM [5]. PFM works by having obstacles create repulsive forces that act on the robot while the target creates an attractive force. The sum of the forces creates a resultant force that determines the optimal direction and speed for the robot. The VFF is a particular type of PFM that uses a histogram grid, a two-dimensional Cartesian grid, for representation of the obstacle. Each cell contains a certainty value associated with the level of confidence that algorithm has with regards to an obstacle’s presence. However, there are inadequacies related to PFM, specifically VFF, that deter the robot from a successful traverse and include trap situations that occur due to local minima, does not create a passage between closely spaced obstacles, oscillations occur in the presence of obstacles and oscillations occur in narrow passages [3].

Time-Varying Potential Field method differs from the original Potential Fields Method in many respects, most notably the use of primarily laser radar versus ultrasonic and laser radar. The Time-Varying Potential Method is also different from the original PFM in that the Time-Varying method the velocity is determined by the environment, and the direction of the robot is controlled by the dynamic potential as opposed to the sum of the forces in PFM. Furthermore, the shapes of obstacles and free space are not of concern, but only referred to as a point obstacle or a point free space [7]. This approach creates a right side potential and a left side potential. The dynamic potential is calculated by summing the potentials on each side. Whereas the velocity is obtained by taking the difference of the dynamic potentials[5]. Issues can arise with regards to the Time-Varying Potential method and its associated laser radars. Such issues include calibration issues, bumping the robot and disorienting sensors, reflective surfaces causing problems with reflecting the light back to the radar, and stray light can cause problems [7]. Other issues that coincide with the Time-Varying method is that scalar quantity is a result of potential, but in determining the velocity angle a vector quantity is more appropriate. Also, this method is not suitable for path planning as it ignores goal orientation [5].

Vector Polar Histogram method (VPH) is a combination and improvement on the VFH and PFM. The VPH method is based on the utilization of laser radar or Laser Measurement System (LMS). The method consists of three steps to achieve the new steering direction. The first and second step formulate a polar histogram and a threshold function based on the obstacle distances. By comparing the threshold function, the polar histogram is reduced to a binary histogram. A series of potential directional candidates can be obtained from the binary histogram and a cost function can be used to find the optimal steering direction. This method takes into account the real-time velocity of the robot, as well as the influences caused by the distribution of angles with the establishment of the threshold function [5].

A dynamic window is another approach to obstacle avoidance that utilizes a short time interval when computing a future steering command. This approach creates trajectories within the short time interval that result in a two-dimensional search space of a combination of rotational and translational velocities. The search space is limited only to velocities allowing the robot to stop safely or to velocities that can be achieved in the next time step. The combination of these velocities forms the dynamic window. The dynamic window approach requires an objective function that consists of the progress relative to the goal location, the forward velocity, and the distance to the next obstacle. The combination of translational and rotational velocities is chosen by maximizing the objective function within the dynamic window. The robot will trade off reaching the desired goal at fast pace for not colliding with the nearest obstacle. This method consists of a two-step algorithm. In the first step, the algorithm presents a space of plausible velocities by only considering velocities that are attainable given the dynamic constraints and that are safe with respect to the close obstacles. In the second step, the algorithm chooses the velocity, or direction, that maximizes the objective function [4].

# **Technical Approach**

A relatively comprehensive evolutionary summation of algorithmic approaches to obstacle avoidance in mobile robotics was previously provided in the literature review section. The methods extensively researched pertained to the suggestions on the handout and to the available literature. The importance of global and local approaches was apparent in the various documents reviewed . For this project in particular, global mapping or a pre-examined environment with stationary obstacles that could be taken into consideration will most likely not be available. The primary concern being immediate, local obstacle avoidance combined with overall area traversed. The most likely successful approach is one that has limited shortcomings with simplistic computations. Having limited knowledge and experience in the area of mobile robotics, specifically obstacle avoidance methods, I wouldn’t be comfortable making the executive decision on the most efficient approach. However, from the published literature I evaluated I’m inclined to advise that the VPH method fits the criteria of having limited defects, as the method has eliminated inadequacies of previous methods, and is relatively simplistic.

# **Past Experience**

I have no past experience with mobile robotics, or affiliated obstacle avoidance approaches, other than what has been covered in the lecture, in the laboratories of the Mobile Robotics course, and the knowledge acquired reading the relevant scientific publications for this proposal.

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