Chapter 5

Dynamic Obstacle Avoidance of USV

Obstacle avoidance without dynamic obstacle is not practical with obstacles on Sea. Dynamic obstacle avoidance is discussed in this chapter in detail. Simulation results relevant to dynamic obstacle avoidance is discussed in the next chapter.

5.1 Introduction to Novel Dynamic Obstacle Avoidance Method

Projected obstacle area method is a very famous method for dynamic obstacle avoidance. Dynamic obstacles can freeze time with the help of that method. Then any type of static obstacle avoidance method can utilize to avoid that. This method is employed in several places on ground and water.

Dynamic obstacle is transformed to another static obstacle which is having large dimensions in the above method. That means it utilized the effective area of the path planning plan which can be employed for path planning. That may be coursed to plan inefficient paths to avoid dynamic obstacles. Then USV may able to travel longer or it may stops suddenly due to lack of effective areas on the path planning plan. So it is very vital to utilize the traveling area effectively as well as avoiding dynamic obstacles. So the novel method is proposed to avoid Dynamic obstacles by employing the minimum areas on the effective area of the path planning plane.

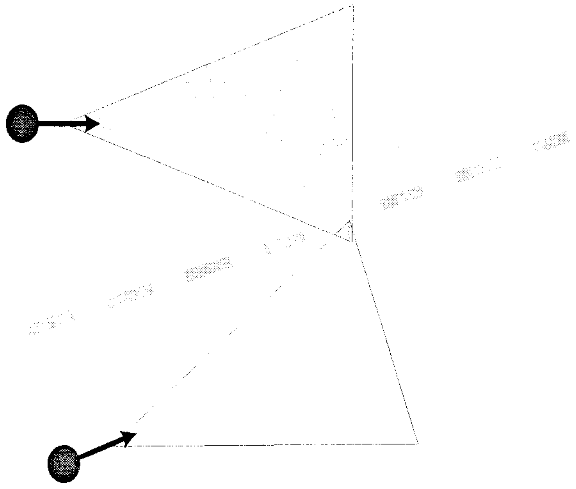

Figure 5.1- Two Dynamic obstacles with Projected Obstacle Areas

Figure 5.1 presents two dynamic obstacles which are freezed with time. Those two predicted areas have blocked the effective path from their edges. The following Figure 5.2 shows the advantage of reducing that predicted areas. So the path planner is generated the efficient path between two obstacle areas.

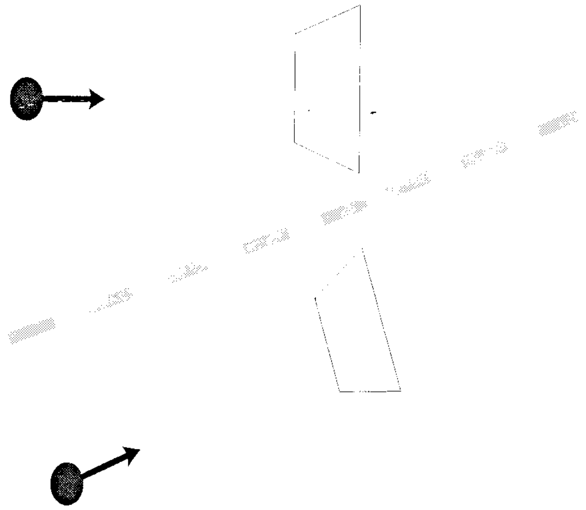

Figure 5.2-Two Dynamic obstacles with their reduced projected obstacle areas

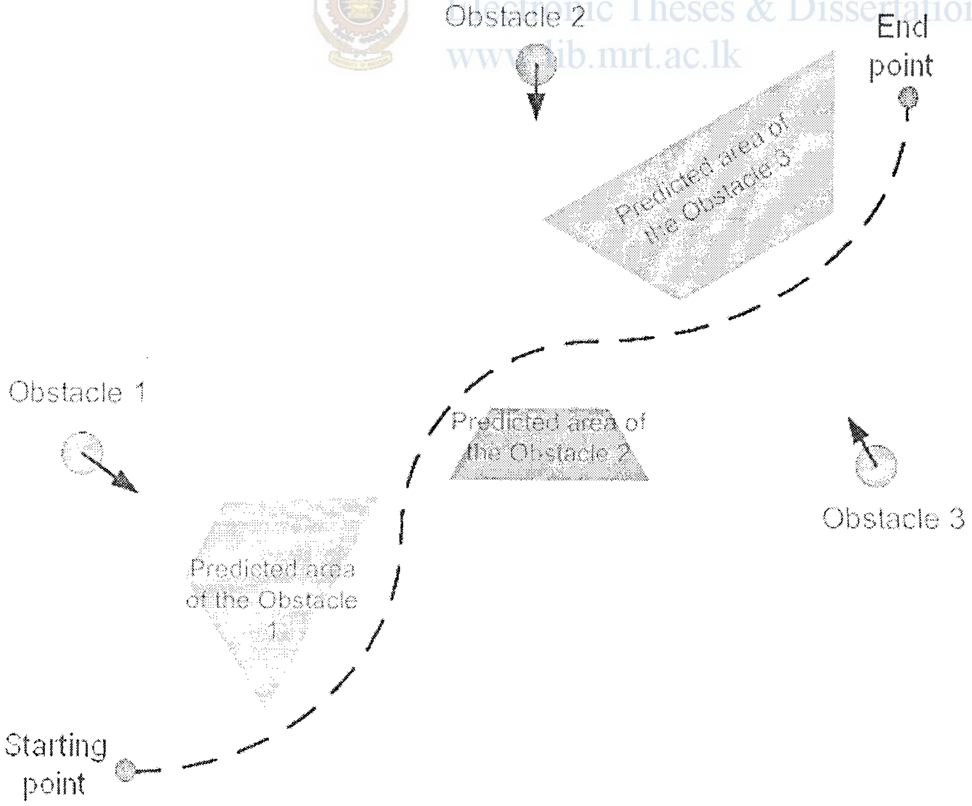

Figure 5.3-Path planning between three dynamic obstacles

Figure 5.3 presents the predicted path among 3 dynamic obstacles. These obstacle areas are generated by freezing 3 dynamic obstacles with time. So the path planner considers those areas as another static obstacle and then it can avoid those by utilizing any static obstacle avoidance method.

5.2 Area Prediction of Dynamic Obstacles

The effective time estimation of Dynamic obstacles is very important to avoid them. Some dynamic obstacles near to USV may not cause any effect on the USV. They may travel away from the USV. Some dynamic obstacles may travel towards the USV. So that it is very important to estimate the effective time of a Dynamic obstacle. The time estimated is presented from t_{area} in Equation 5.2 . Equation 5.1 is utilized to calculate T after reveling t_1 and t_2 . t_1 is calculated making use of the velocity of the obstacle while t_2 is calculated by employing velocity of the USV. t_2 is the time taken to the USV to cross the predicted path of a moving obstacle while t_1 is the time taken for that moving obstacle to cross the defined path of the USV. The traveling path of the USV is known before hand and has to utilize a path prediction module to predict the path of obstacles.

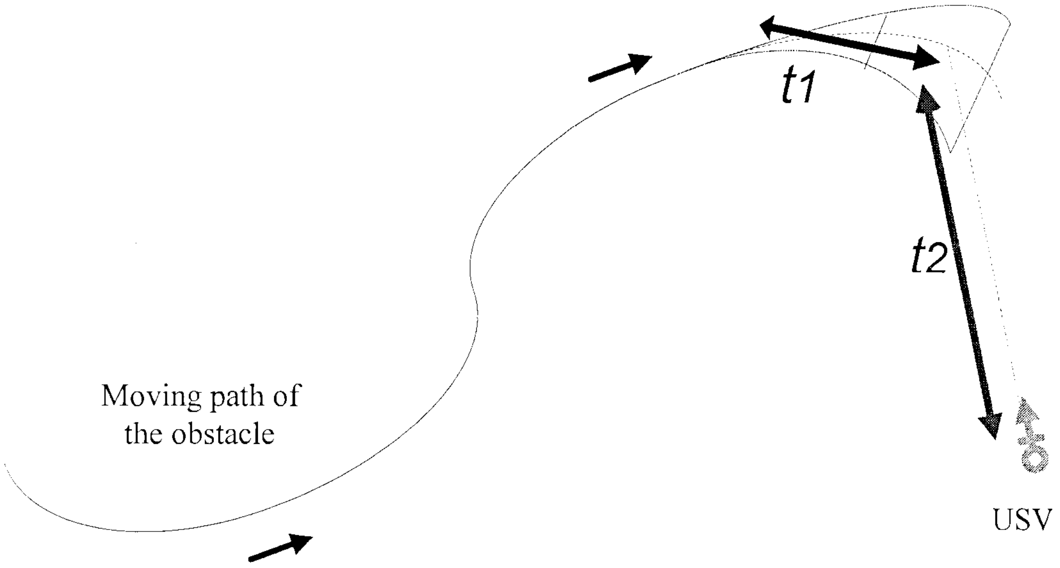

Figure 5.4-Effective time prediction of Dynamic obstacles

$$T = \frac{\Phi}{|t_1 - t_2|} \quad \text{-------------------------------(5.1)}$$

$$t_{area} \in \left[\left(t_1 - \frac{T}{2}\right), \left(t_1 + \frac{T}{2}\right)\right] \quad \text{--------------------------------(5.2)}$$

Where t_2 is the time taken to the USV to cross the predicted path of a moving obstacle, t_1 is the time taken for that moving obstacle to cross the defined path of the USV

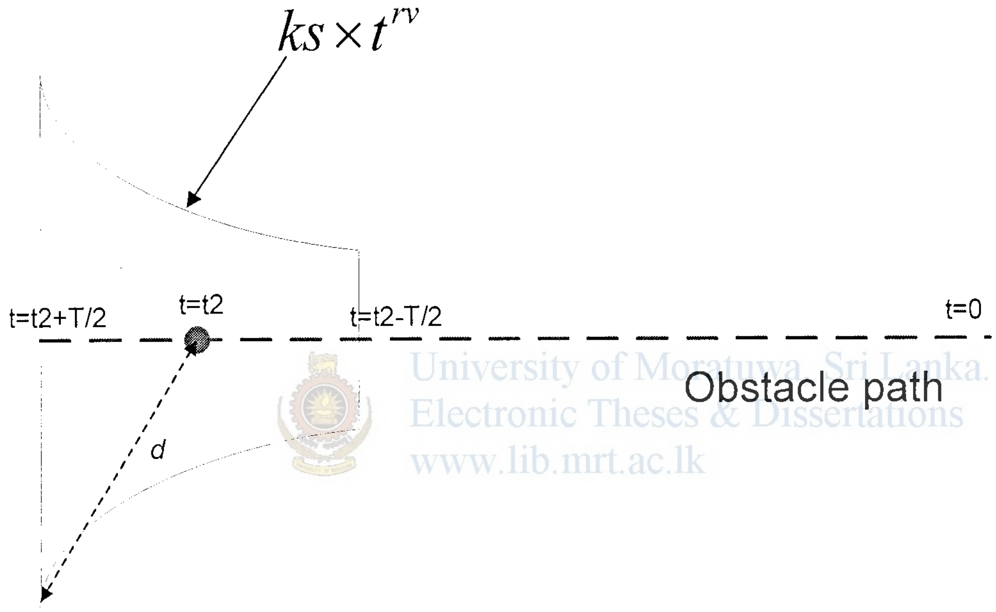

Figure 5.5- Area Calculations for Dynamic obstacle

Figure 5.5 presents the area calculation of Dynamic obstacles. That area is depending on the relative velocity of the obstacle as well. K is chosen depending on the sea. Because the behavior of the obstacle is directly depend on the sea condition as well. The obstacle movement is very high on a ruff Sea. So that predicted areas for obstacles on a ruff sea should be comparatively larger than a normal Sea. High velocities are increasing the possibility of high deviations from the predicted paths. The importance of the obstacle velocity to the predicted area is reflected through new equation well. The constant in the above equations can be change at the practical implementation phase. The dimensions of that area can be changed by changing the constant in the above equation.

5.3 Path Prediction of Dynamic Obstacles

It is very important to determine the path of dynamic obstacles to avoid them. Radars and other obstacle detection methods can utilize to take moving coordinates of the obstacles. Then those data are stored in an array. So, that array can utilized those data to predict the future movements of the obstacles in the next step. It is required to store lateral and longitudinal coordinates with time for path prediction purpose. It is quite complex thing to analyze. So two separate arrays consisting lateral coordinates with time and longitudinal coordinates with time are utilized for analyzes. Figure 5.6 presents a simulation result showing the actual and predicted path in 3-D space.

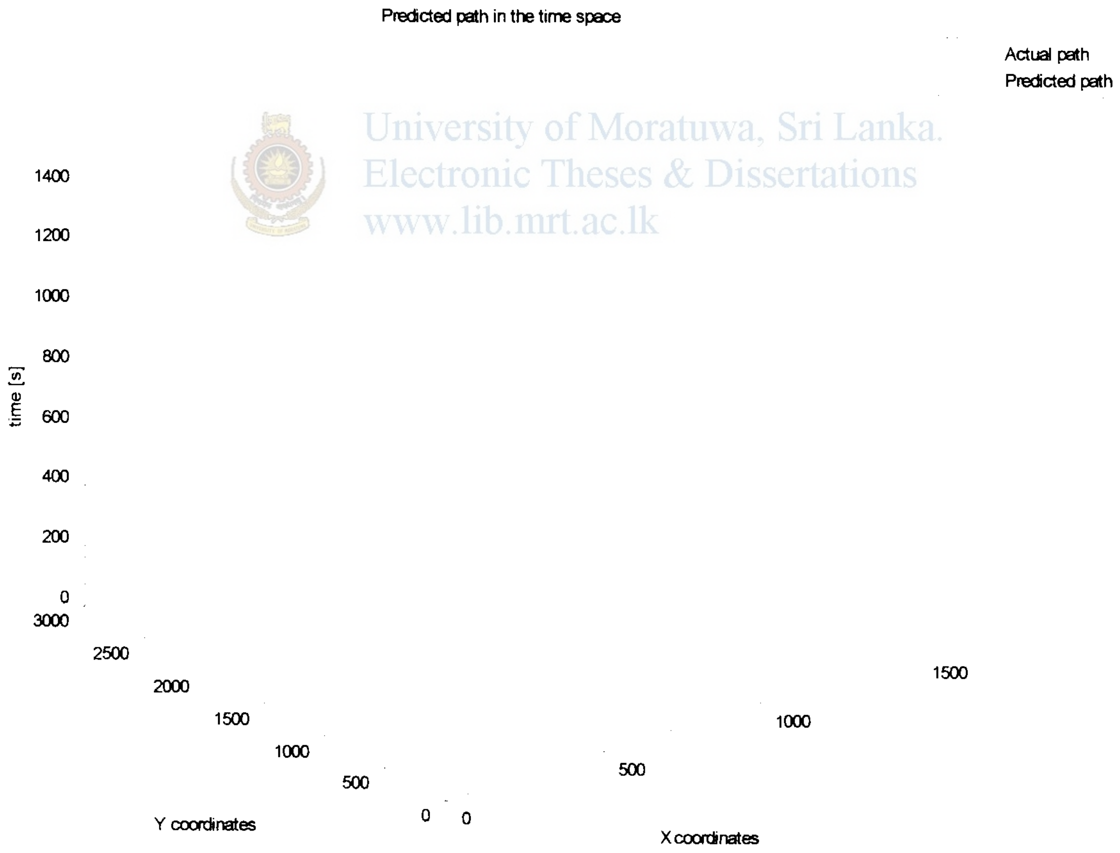

Figure 5.7-Simulation result of an Actual and Predicted path in 3D space

Two prediction methods are utilized for path prediction in this study. First conventional mathematical method is attempted and then generalized regression neural network (GRNN) method is employed [26, 9]. All the results are collected and analyzed at the end.

5.3.1 Polynomial Approximation Method for Path Prediction

Conventional mathematical method, polynomial approximation is utilized to predict the moving path of the obstacles first. The data array which was utilized to store initial positions of that obstacle is taken to approximate the moving function of the obstacle. Two functions have approximates for lateral movement and longitudinal movements. Then those two polynomial functions are employed to predict the path of the obstacle. Several arrays can be employing easily for several Dynamic obstacles as explained earlier. The difference between predicted and actual path is analyze by changing the degree of the polynomial. Obviously the sensor noise cannot be neglected as it is part of the actual data. Because the GPS and Rader data having their own deferent noise. So sensor noise is added to the data and analyzed at the end.

5.3.2 Generalized Regression Neural Network for Path Prediction

GRNN is often used for function approximation. It has a radial basis layer and a special linear layer. It consists of two-layer network. The first layer has radial basis neurons and the second layer has linear neurons [9].

MatLab Neural Network tool box is utilized for the simulations of this study. It is customized by changing the variable name ‘spread’.

A larger ‘spread′ leads to a large area around the input vector where layer 1 neurons will respond with significant outputs. Therefore if ‘spread′ is small the radial basis function is very steep, so that the neuron with the weight vector closest to the input will have a much larger output than other neurons. The network tends to respond with the target vector associated with the nearest design input vector.

As ‘spread′ becomes larger the radial basis function's slope becomes smoother and several neurons can respond to an input vector. The network then acts as if it is taking a weighted average between target vectors whose design input vectors are closest to the new input vector. As ‘spread′ becomes larger more and more neurons contribute to the average, with the result that the network function becomes smoother.