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Multi-Sensor Data Fusion used in Intelligent Autonomous Navigation

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1) Introduction

Several types of sensors have been utilized for autonomous navigation Radar, laser range finder , Forward looking Infra Red (FLIR),day light camera, sonar sensors, GPS, Gyro compass,... are in this category .Such sensors have been involved during recent years , but the navigation system for vessels and ships (our case study) is still manual for supervising, data acquisition and processing.Manual methods always confront some mistakes and in some cases it is needed to guide thevehicle without human aids.In such condition an autonomous navigator should be installed on the vessle.Such navigator utilizes the data logged from sensors in a Data Fusion System (DFS) to estimate the location of obstacles which are eigther dynamic or static and also, under water or floating .

Since these informations are instantly variable, the vessle should be guided toward the target instantly as well. Defining a potential function has been the major method used for autonomous guidance and collision avoidance.If we move against the gradient of potential function ,i.e. $-\nabla\phi$, we will approach to the target [1,2,3].

Potential & other general classical methods have some deficiencies such as:

1. All calculation, must be basically updated to detect a new obstacle.

2. Gradient claculation is time consuming and inexact.

3. Trapping of navigation in a local minimum halts the operation of the system.

In the proposed navigator ,several simple and separate controllers opearate independently and finally a decision system utilizes these controllers to guide the vessle.

2) Navigation system

The navigator could use "Rudder","Speed" commands to control the trajectory of the vessle inside the sea. Navigator must control the vessle in such a manner that it moves toward the target as fast as and as safe as possible.Assume that the vessle voyages from "origin" toward the "target" and the obstacles { O1,O2,...On } existe in the environment.As long as the vessle approaches the neighbourhood (critical) area of any obstacle , the navigator should change the path to avoid collision.

The block diagram of navigation system is shown in figure(1).The navigator is an intelligent fuzzy controller and controls the vessle using " If Then " rules .In this system the location,speed,state and dangerness degree of every obstacle are stored in a shared memory ,this memory is updated in each time interval.The navigator uses this shared memory to obtain the number of obstacles and their attributes.In each update, if there is a new object in the environment,the navigator constructs a new controller to avoid collision ,and in the same manner,if an object is removed from the environment , the navigator removes the correspponding controller . Obviously,in this system there are several

controllers, each constructed to avoid collision with a the corresponding obstacle. These controllers operate separately and depend just on the attributes of their associated obstacles.

In addition to these controller, there is another controllers which guides the vessel toward the target.

Each controller has two outputs "Speed" , "Rudder" , which are the main commands signals to the vessel motion dynamics. these outputs must be fused according to the strength of their associated controllers. Which will be explained more in the next section.

2.1) Controller for guidance toward the target

This controller forces the vessel to reach the target . According to the figure(2) Suppose that the vessel is in the location P, some fuzzy rules which control the vessel are listed below.

- if (α is left) & (\mathbf{d} is long) \Rightarrow Rudder = right
- if (α is zero) \Rightarrow Rudder = zero
- if (\mathbf{d} is near) & (α is zero) \Rightarrow Speed = low
- if (\mathbf{d} is long) \Rightarrow Speed = high

in which α , \mathbf{d} are input variables to the controller and "speed" , "Rudder" are its output variables , applied to the vessel. After defuzzification of the rule , each rules proposes two values for "speed" , "Rudder" ($\check{\alpha}Speed_{ij}$, $\check{\alpha}Rudder_{ij}$) , and final proposed value are computed as

$$\check{\alpha} Rudder_t = MAX(\check{\alpha} Rudder_{ij})$$

$$\check{\alpha} Speed_t = MIN(\check{\alpha} Speed_{ij})$$

t: target j: Fuzzy rule (i.e. mf) index

in addition to these values, the strength of the controller mf_i is defined as

$$\mu_{ii} = \mu(A_{ij} \Rightarrow B_{ij})$$

$$mf_i = Max(\mu_{ij})$$

where mf represents the strength of this controller and its degree of truth. This concept plays a major role in the fusion of the outputs of the controllers. This will be explained in more details in section 2.3 .

2.2) Obstacle avoidance controller

The same as previous section , two parameters ($Speed_{ij}$) , ($Rudder_{ij}$) are defined according to figure

2 and there are some rules which avoid collision with a certain obstacle .

- if (β is left) & (d_s is near) \Rightarrow Rudder = left
- if (β is left) & (d_s is far) \Rightarrow Rudder = zero
- if (β is left) & (d_s is near) \Rightarrow Speed = low
- if (d_s is long) \Rightarrow Speed = high

The variables "Speed" , "Rudder" , given by:

$$\check{\alpha} Rudder_t = Max(Rudder_{ij})$$

$$\check{\alpha} Speed_t = Min(Speed_{ij})$$

i: obstacle index j: Fuzzy rule (i.e. mf) index

are output values which this controller provides .

Furthermore the output mf_i is defined as :

$$mf_i = Max(\mu(A_{ij}))$$

which represents the strength of the ' i th ' controller to avoid collision with the ' i th ' obstacle.

2.3) Fusion of controllers

Each of existing controllers offers two values for "Speed" and "Rudder" and

a strength value as mf. These values will be fused by the weighted mean operator as follows::

$$Rudder(final) = \frac{\sum (Rudder_i * mf_i) + Rudder_t * mf_t}{\sum mf_i + mf_t}$$

$$speed(final) = \frac{\sum (speed_i * mf_i) + Rudder_t * mf_t}{\sum mf_i + mf_t}$$

These two final values are applied to the vessel . some simulation results are shown in figure 4,5.

3) Multi Sensor Data Fusion (MSDF):

To estimate the exact position of the obstacles several sensors are utilized such as Radar, Laser Range Finder, FLIR (Forward Looking Infra Red), Each sensor properly works in a certain situation or in a certain range , for example angle report of a FLIR system is more accurate comparing with RADAR System , To obtain a reliable and more accurate information about obstacles positions the information obtained from different sensors should be fused [5,6].

MSDF system is shown in figure(3). In this system , there are n reports from n different sensors.

In this system , kalman filter has been used to obtain better estimate of obstacle position .

The kalman filter algorithm is quite general and straightforward, however, its implementation generally relies on good engineering judgement and process parameter estimation . These parameters are system model and system states and measurement

covariances . These parameters must be tuned and adjusted in each time step .

Analytical methods exist to find the system covariance matrix $Q(k)$ [2,10],but such methods are difficult to implement in practice .

In this work we find elements of $Q(k)$ by training an artificial neural network.

Assume that system model is defined as follows :

$$X(k+1) = F X(k) + B U(k) + V(k)$$

$$Y(k) = H X(k) + W(k)$$

$$E(V V^t) = Q(k), \quad E(W W^t) = R(k)$$

Assume that the input is constant or slowly changing Then we can write

$$X(k+1) - F X(k) = B U(k) + V(k)$$

$$E(X(k+1) - F X(k)) = E(B U(k)) + E(V(k)) = B U(k)$$

and the system equations can be written as :

$$X(k+1) - F X(k) + E(X(k+1) - F X(k)) = V(k)$$

The estimation system in fig 3 is constructed according to the above equations.

In this system a block has been used to estimate the $E(X(k+1) - F X(k))$ and the other one is used to estimate the $E(V(k) V(k)^t)$.

The estimated Q is fed to Kalman Filter to update the Q matrix and consequently produce better state estimation .

In the proposed MSDF system , due to on-line process parameters estimation and adjustment , Kalman Filter estimates the obstacles positions more accurate than the ordinary simple and stationary Kalman Filter.

3) Simulation results

Simulations have been performed for a simple boat[8]. In the first case study there are just two obstacles without any uncertainties about them. In the second case study , position uncertainties are introduced and in the third case study multiple obstacles are considered.

figure 4 shows the route of the boat from origin toward target.As the boat approaches the dangerous (critical) area,proportional to the degree of importance,distance and other characteristics of the obstacle,the navigator reduces the speed and changes the trajectory.After passing the obstacle,the boat returns to its primary direction toward the target

,since the associated controller for this behaviour has the most power.

Figure 5 shows the activity of controllers during path planing.

Figure 6 shows path planing in presnce of uncertainty in sensor readings.

Figure 7 shows the path planing in a crowded area.

Figure 8 shows the speed diagram ,which changes during path planing

Figure 9 shows estimation of state covariance.The bold line indicates the real $Q(k)$ and the other indicates the estimated state covariance which is fed the kalman filter.

Figure 10 indicates the sensor reports and real ship path before fusion process, and in figure 11 shows the estimated path produces by Kalman filter after fusion process.

4) Conclusion

The advantages of the proposed method respect to other existing navigation can be discussed from several viewpoints. Due to the decentralized structure of these controllers , fusion of their commands is very easy .The other new idea ,is the introduction of Fuzzy power for each controller and efficient using of this fuzzy variables in fuzzy rules and in the weighted combination of controller outputs.These two ideas have no past record in conventional fuzzy methods for control,specially intelligent path planing .The main dvantages for our method are:

1. The navigation system requires just the location of "origin" and "target" , i.e. it is not necessary to have a lot of knowledge about the navigation environment such as a global or local map.

2. The navigation mechanism works on-line i.e. if an unpredicted obstacle (static or moving ;but moving slowly) appears in the environment , the path will be defined so as to avoid collision,so,it is not necessary for all obstacles to be predefined.

3.The introduced speed variable of the vehicle ,increases the potential for maneuvering, the safety of the motion , comparing to the other existing navigation systems which neglect from system variable.

4.Finally,the existance of the uncertainties in localizations of vessle ,obstacles and target have no significant effects on navigation performances.

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Obstacle position recieved from sensors

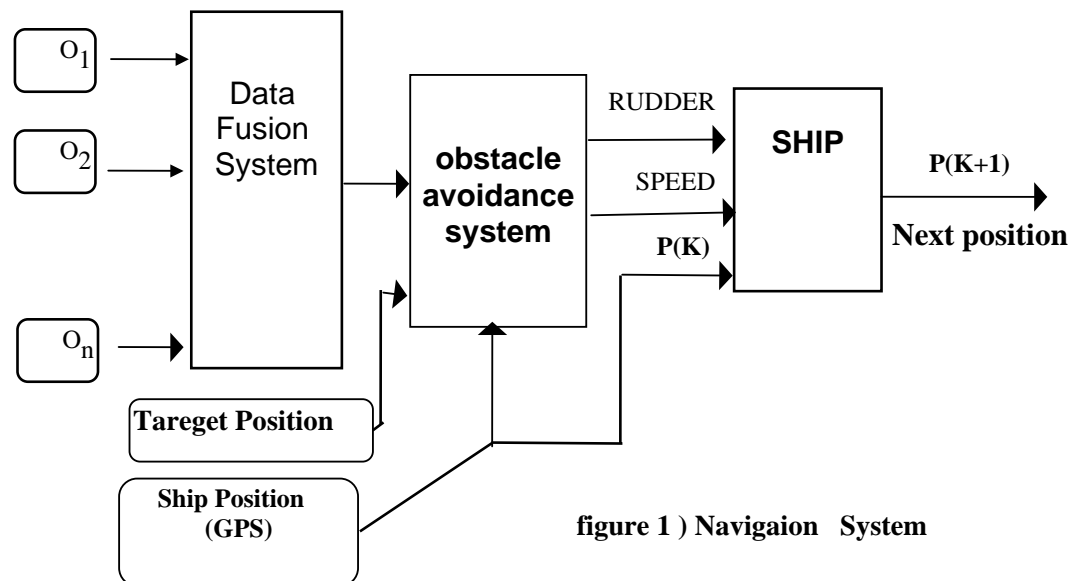
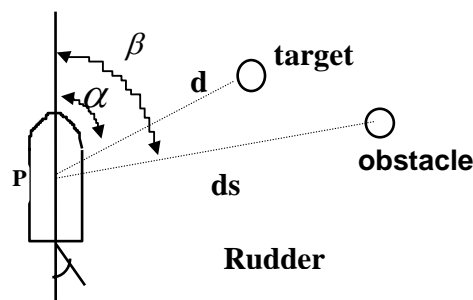


figure 1) Navigaion System

figure 2) Variable definitions



Rudder