Supervisory Fuzzy Learning Control for Underwater Target Tracking

C.Kia, M.R.Arshad, A.H.Adom, and P.A.Wilson

***Abstract*—**This paper presents recent work on the improvement of the robotics vision based control strategy for underwater pipeline tracking system. The study focuses on developing image processing algorithms and a fuzzy inference system for the analysis of the terrain. The main goal is to implement the supervisory fuzzy learning control technique to reduce the errors on navigation decision due to the pipeline occlusion problem. The system developed is capable of interpreting underwater images containing occluded pipeline, seabed and other unwanted noise. The algorithm proposed in previous work does not explore the cooperation between fuzzy controllers, knowledge and learnt data to improve the outputs for underwater pipeline tracking. Computer simulations and prototype simulations demonstrate the effectiveness of this approach. The system accuracy level has also been discussed.

***Keywords*—**Fuzzy logic, Underwater target tracking, Autonomous underwater vehicles, Artificial intelligence, Simulations, Robot navigation, Vision system.

I. INTRODUCTION

AUVs are multi-function platforms with navigation requirements which depend highly on a specific mission and sensor suite onboard. It is entirely feasible that for a given suite of sensors, the vehicle can navigate adequately for one mission, but fail to meet the minimum requirements for another mission [1].

A tracking component is essential to continuously manoeuvre the vehicle over a structure (e.g. pipeline). If the pipeline is lost (for instance due to being buried) the intelligent tracking system must be able to adapt to this condition and navigate the vehicle to the correct route of the pipeline [2].

Due to underwater optical behaviour, there are also many occasions where the submarine cable is not visible enough for the vision processor to track the cable. In addition, the environment makes the cable invisible with time due to growth of underwater plants etc. [3].

No a single type of AUV control system is able to solve all the tracking problems, but each type of problem has its own solution, normally specific to a particular application. This paper reports our ongoing work in improving the robustness and correctness of AUV tracking on occluded pipeline based on visual input.

This paper is structured as follows. Section II reviews the previous work completed on the underwater target tracking system. Section III describes the methodology of the work. Section IV discusses the simulations procedure and results. While section V summaries the work presented with the conclusion of the paper.

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II. REVIEW OF PREVIOUS WORK

This section briefly describes our previous research work on control strategy and the motivation to improve its tracking robustness and correctness. The work is summarized as follows [4]:

a) A vision system is developed which is capable of interpreting the underwater scene by extracting subjective uncertainties of the object of interest (i.e. pipeline images)
b) Subjective uncertainties are further processed as multiple inputs of a fuzzy inference system that is capable of making crisp decisions concerning where to navigate.
c) The system has been fully tested and the results are favourable (i.e. the results drifted within the tolerance limits).
d) However, the images captured contain clear and visible pipeline, which made the correct inputs fed to the fuzzy inference system possible.
e) Considering the practical aspect, visibility of underwater pipeline may not be available due to uncertain underwater conditions. Under these conditions, the system output may not be favourable anymore. Hence, it is reasonable to conduct further investigations for a better technique.

III. METHODOLOGY

The proposed system consists of image processing operations and basic fuzzy inference systems enhanced by a supervisory fuzzy learning control technique. The image processing operations produce high-level information that is actually the morphological parameter for the input of a fuzzy inferences system (linguistic representation of terrain features).

Consider the situation illustrated by Fig.1. The illustration shows the system setup from plan view whilst the AUV is actually looking at the pipeline from its perspective view. The fuzzy logic is utilized to interpret this heuristic in order to generate the steering command set point. In this case, the set point of the AUV has a certain amount (ΔX) to the right.

The basic steps of the algorithms are as follows:

a) Load RGB image and convert it into grey scale image.
b) Perform thresholding to binaries the image.
c) Label connected region and search for the largest connected region.
d) Perform deletion of unwanted connected region and the largest connected region is extracted as object of interest.
e) Perform image segmentation by dividing it into 5 segments and be processed separately for terrain features as multiple steps of inputs for the fuzzy controller.

f) In order to investigate more closely each specific area within the image segment, each segment is further divided into 6 predefined sub segments in the image as illustrated in Fig.2.
g) Calculate the area for each sub-segment.
h) The area is accumulated as multiple inputs of fuzzy inference system.
i) Apply fuzzy operators.
j) Apply implication method.
k) Aggregate all output fuzzy sets.
l) De-fuzzification.
m) Generate decision. The fuzzy output is a crisp value of the direction for navigation (decision on control action).
n) Accumulate generated decision as learnt knowledge (data).
o) Apply fuzzy controller supervisor to monitor if the pipeline occluded.

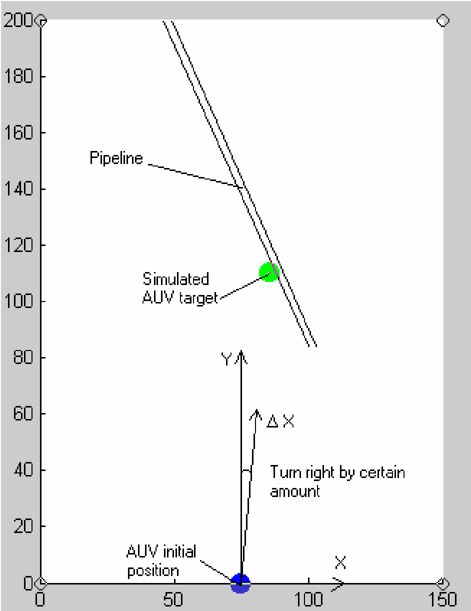

Fig.1 Illustration of tracking strategy

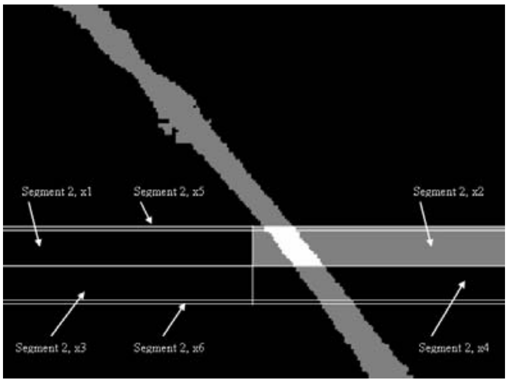

Fig.2 Illustration sub segment

The fuzzy inference system developed has 6 inputs, 1 output and 13 rules. The inputs are defined as follows:

x_1 = Pipeline area at upper left sub segment within specific segment allocated in the image
x_2 =Pipeline area at upper right sub segment within specific segment allocated in the image
x_3 = Pipeline area at lower left sub segment within specific segment allocated in the image
x_4 =Pipeline area at lower right sub segment within specific segment allocated in the image
x_5 =End point of pipeline relative to image center point
x_6 =Beginning point of pipeline relative to image center point

The output variable is defined as follows:

y_1 = AUV steering command set point

The fuzzy rules are as follows:

(x_5==Negative)&(x_6==Positive)=>(y_1=Turn_Left)
(x_5==Positive)&(x_6==Negative)=>(y_1=Turn_Right)
(x_2==Small)&(x_4==Small)=>(y_1=Turn_Right)
(x_1==Small)&(x_3==Small)=>(y_1=Turn_Left)
(x_5==Positive)&(x_6==Positive)=>(y_1=Turn_Right)
(x_5==Negative)&(x_6==Negative)=>(y_1=Turn_Left)
(x_5==Centre)&(x_6==Centre)=>(y_1=Go_Straight)
(x_5==Negative)|(x_6==Negative)=>(y_1=Turn_Left)
(x_5==Positive)|(x_6==Positive)=>(y_1=Turn_Right)
(x_2==Medium)&(x_4==Medium)=>(y_1=Turn_Right)
(x_1==Medium)&(x_3==Medium)=>(y_1=Turn_Left)
(x_2==Large)&(x_4==Large)=>(y_1=Turn_Right)
(x_1==Large)&(x_3==Large)=>(y_1=Turn_Left)

The dependency of some of the outputs on the two of the inputs is generated and plotted as output surface map as shown in Fig. 3, Fig. 4 and Fig. 5.

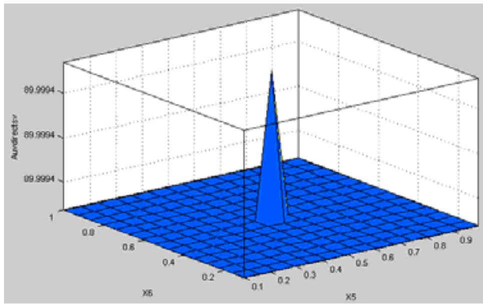

Fig.3 Output surface map for x_5 and x_6

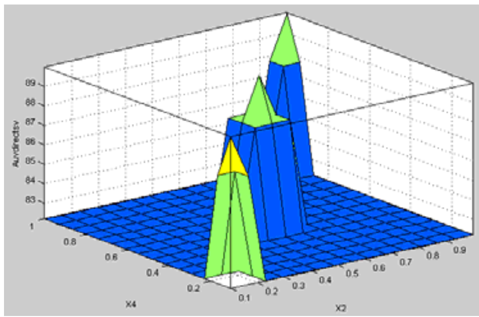

Fig.4 Output surface map for x_2 and x_4

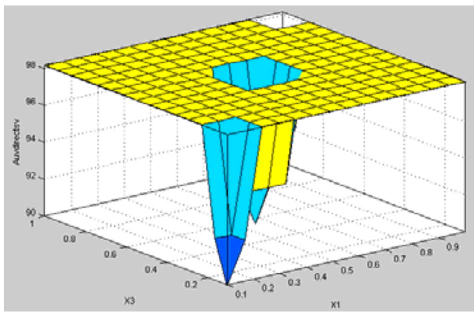

Fig.5 Output surface map for x_1 and x_3

The pipeline is considered occluded when no area information is acquired as input to the fuzzy inference system. The example of occluded pipeline is shown in Fig.6. The fuzzy controller supervisor will use general rule that the pipeline is straight [5], hence use past learnt data from previous fuzzy output to perform linear extrapolation to replace the fuzzy output.

Fig.6 Typical examples of occluded pipeline

IV. Simulations and Results

In the simulation stage, the process was started by defining the underwater working area of prototype on a grid of coordinates, 150.0cm x 200.0cm max. The pipeline is then determined and measured for its real position and orientation according to the grid of coordinates. The measurements are taken as reference to the simulated outputs. The simulated AUV navigating paths are recorded and visualized graphically. The results are quantified and analyzed using correlation coefficient, simple mean and simple median. The equation for the correlation coefficient is [6]:

$$\rho_{x,y} = \frac{Cov(X,Y)}{\sigma_x, \sigma_y}$$

where

$$Cov(X,Y) = \frac{1}{n}\sum_{j-1}^{n}(x_j - \mu_x)(y_j - \mu_y)$$

The equation for simple mean is [6]:

$$X' = \frac{1}{n}\sum_{j-1}^{n} x_j$$

The equation for simple median is [7]:

$$M = \begin{cases} X_{(k)} & (even, n = 2k) \\ \frac{1}{2}[X_{(k)} + X_{(k+1)}] & (odd, n = 2k-1) \end{cases}$$

To evaluate the performance, significant trials, have been carried out. The simulated output results after the implementation of supervisory fuzzy learning control technique is compared with the simulated output results from the decision of basic fuzzy controller. Here we only present one typical example.

A. Simulated Output Resulted by Basic Fuzzy Controller

Fig.7 and Table 1 showed the simulated navigation command output for tracking an occluded pipeline without the implementation of supervisory fuzzy control technique. In this case, the occluded pipeline is found in path no. 4 with the command output drifted away for as far as 21.9cm.

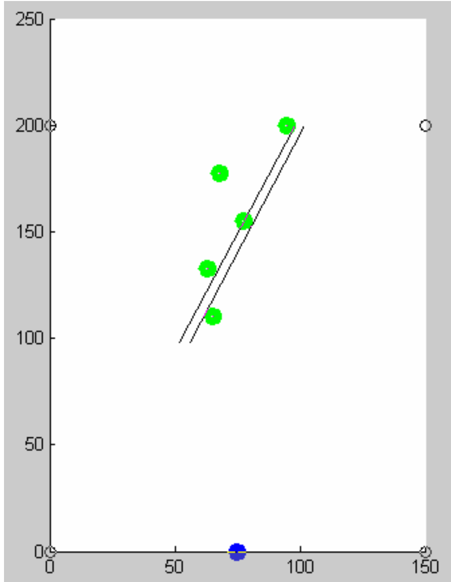

Fig.7 Simulated AUV path without fuzzy supervisor

TABLE I
Data Recorded without Fuzzy Supervisor

AUV path	Actual location x-axis (cm)	Simulated output x-axis (cm)	Drift (CM)
5	100.0	94.8	-5.2
4	89.9	68.0	-21.9
3	79.8	77.5	-2.3
2	69.7	63.1	-6.6
1	59.6	65.3	+5.7

The statistical results are as follows:
Correlation coefficient: 0.777736
Arithmetic mean for simulated output: 73.7cm
Median for simulated output: 68.0cm
Arithmetic mean for actual location: 79.8cm
Median for actual location: 79.8cm

B. Simulated Output Resulted by Supervisory Fuzzy Learning Controller

Fig.8 and Table 2 showed the simulated navigation command output for tracking an occluded pipeline with the implementation of supervisory fuzzy control technique. The fuzzy supervisor generates the occluded pipeline in path no. 4 with the command output drifted away for only 2.0cm.
The statistical results are as follows:
Correlation coefficient: 0.948069
Arithmetic mean for simulated output: 78.5cm
Median for simulated output: 77.5cm
Arithmetic mean for actual location: 79.8cm
Median for actual location: 79.8cm

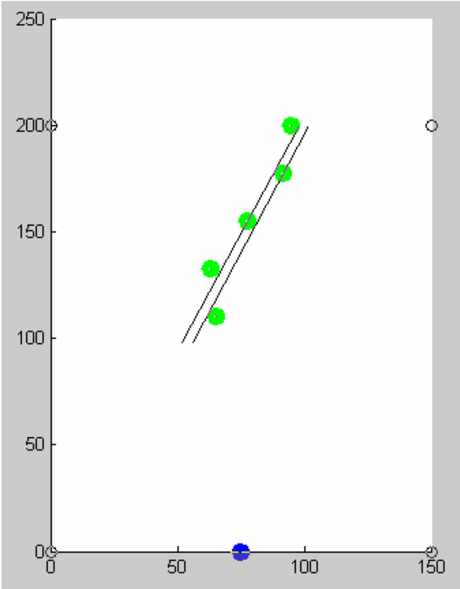

Fig.8 Simulated AUV path with fuzzy supervisor

TABLE II
DATA RECORDED WITH FUZZY SUPERVISOR

AUV path	Actual location x-axis (cm)	Simulated output x-axis (cm)	Drift (CM)
5	100.0	94.8	-5.2
4	89.9	91.9	+2.0
3	79.8	77.5	-2.3
2	69.7	63.1	-6.6
1	59.6	65.3	+5.7

C. *Simulated Output Resulted by Basic Fuzzy Controller*

The RGB image size is 39790 pixels where the image width is 230 pixels and image height is 173 pixels. By applying this image resolution to the system, we are able to obtain the result as presented. We would expect the results to be more accurate when an image with higher resolution is used.

However, handling images with higher resolution require more computer memory resources. It is important to note that this project requires merely approximate image information for the fuzzy inputs (i.e.: small area, medium area, large area, negative location, center location, or positive location). Thus, we can conclude that based on the results presented, the image resolution selected is able to provide accurate results.

V. CONCLUSION

In this paper, we have presented an improvement on the control strategy in underwater target tracking and navigation. Clearly, the robustness of the method has improved. The research reveals the potential of implementing supervisory fuzzy learning controller in the application of underwater pipeline tracking. The system is able to continuously learn knowledge (data) and improve the navigation decisions.

The fuzzy supervisor uses any available data from the control system to characterize the system's current behaviour so that it knows how to change the controller and ultimately achieve the desired specifications [8].

We have found the method to be very practical and have great potential usefulness for application in AUV target tracking.

A. *Systems limitation and implementation issues*

The proposed system is demonstrated by a prototype and the algorithm is developed in a simulation software. When it comes to implementing a real time fuzzy control system, we would estimate facing the following problems:

a) Long computation time due to unsuitable processor and no optimization of code structure.
b) Sensors and actuators interfacing problems due to unsuitable controller hardware.

B. *Possible future work for improvements*

5.1 In this research a pragmatic and experimental approach has been adopted to evaluate and confirm the applicability of the implementation of supervisory fuzzy learning controller in underwater target tracking. However, there are some practical aspects that suggested require further investigations. They are:

a) The study of suitable hardware to be implemented for real time control. The hardware should include combination of the camera, frame grabber, fuzzy processor, controller, sensors and actuators.
b) The study of possible underwater hydrodynamic parameters (which requires more sensors) to be integrated into the fuzzy inference system. The hydrodynamic force naturally creates a very uncertain and unpredictable noise and it is recommended that the integration to be studied after suitable hardware is being implemented with acceptable and proven performance.
c) To further investigate and enhance the systems intelligence such as adaptive and auto-tuning capability for the fuzzy controller.
d) To incorporate other established techniques such as artificial neural network and expert system into the existing fuzzy inference system.

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