MODEL PREDICTIVE CONTROL OF AN AUTONOMOUS UNDERWATER VEHICLE

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Abstract: This paper investigates the application of model predictive control to the yaw angle of an autonomous underwater vehicle. A simple line of sight guidance scheme is utilised to generate the reference heading, which is to be followed. Simulation results are presented to demonstrate the suitability of the proposed algorithm. *Copyright © 2002 IFAC*

Keywords: Model predictive control, autonomous underwater vehicle, guidance, genetic algorithm, navigation.

1. INTRODUCTION

Autonomous underwater vehicles (AUVs) are no longer engineering curiosities. They have been under development for over three decades and in the last few years there have been significant advances towards their use in operational missions (Millard, *et al*., 1998). Although remotely operated vehicles (ROVs) play an important role in the offshore industry, their operational effectiveness is limited by the tethered cable and the reliance and cost of some kind of support platform. Given these limitations, developments in advance control engineering theory and the computation hardware for analysis, design and implementation, interest in the viability of employing AUVs in operational missions has been revived. The use of AUVs is increasingly being considered for applications such as cable/pipeline tracking, mines clearing operations, deep-sea exploration, feature tracking etc. The potential usage of AUVs is restricted by two main factors. The first is the limitation of battery power, which confines the AUVs for long duration missions. Most of the vehicles in use, uses car batteries that need to be recharged every few hours and that makes them unsuitable for long duration missions. The second limiting factor is associated with the current generation of onboard navigation, guidance and control (NGC) systems. The vehicle must have a reliable and well-integrated NGC system of which control is the key element responsible for keeping the vehicle on course. On the other hand, navigation

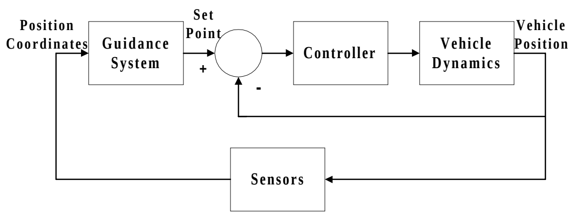

Fig. 1. Navigation, guidance and control of a vehicle

systems provide information related to the target and vehicle itself, using on-board sensors such as inertial navigation system (INS), compass, pressure transducer etc. This information is fed to the guidance system which by utilising some guidance law generate reference trajectories. A simple block diagram of the navigation, guidance and control system is depicted in Fig. 1.

Several classical and advance control strategies have been simulated and tested on an AUV, Craven (1999). In this paper, a new control strategy using model predictive control (MPC) is developed and simulated on an AUV to track the reference heading provided by a guidance system. MPC is chosen because of several reasons one of which, is the ability to handle constraints in a natural way. A genetic algorithm (GA) is used as an optimisation tool to aid in designing the controller which is motivated from the work of Duwaish and Naeem (2001).

The paper is organised as follows. Section 2 explores model predictive control and genetic algorithms. Problem formulation is described in Section 3 while Section 4 presents the simulation results. Finally, concluding remarks are given in Section 4.

2. MODEL PREDICTIVE CONTROL

MPC refers to a class of algorithms that compute a sequence of manipulated variable adjustments in order to optimise the future behaviour of a plant. Originally developed to meet the specialised control needs of power plants and petroleum refineries, MPC technology can now be found in a wide variety of application areas including chemicals, food processing, automotive, aerospace, metallurgy, and pulp and paper, (Qin and Badgewell, 1997).

The development of MPC can be traced back to 1978 after the publication of the paper by Richalet *et al*. Then Cutler and Ramaker from Shell Oil in 1979, 1980 developed their own independent MPC technology "Dynamic Matrix Control". The most popular form of predictive control called the generalized predictive control has been devised by Clarke *et al.,* (1987a, b) and is employed in this paper.

The process output is predicted by using a model of the process to be controlled. Any model that describes the relationship between the input and the output of the process can be used. Further if the process is subject to disturbances, a disturbance or noise model can be added to the process model. In order to define how well the predicted process output tracks the reference trajectory, a criterion function is used. Typically the criterion is the difference between the predicted process output and the desired reference trajectory. A simple criterion function is

$$J = \sum_{i=1}^{H_p} [\hat{y}(k+i) - w(k+i)]^2 \qquad (1)$$

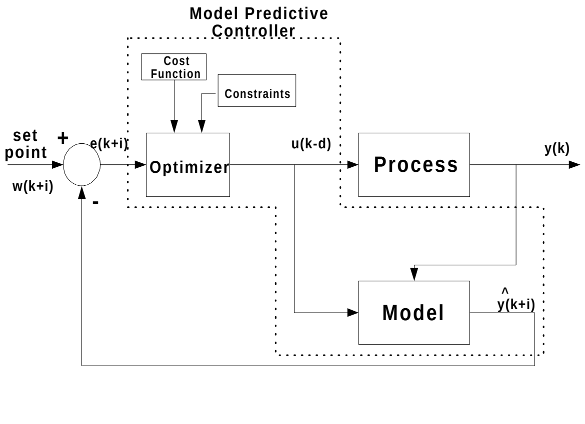

Fig. 2. Structure of Model Predictive Control

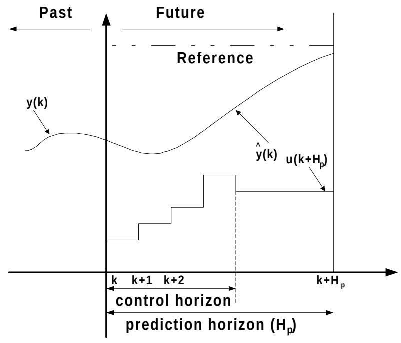

Fig. 3. Predicted output and the corresponding optimum input over a horizon H_p, where $u(k)$, optimum input, $\hat{y}(k)$, predicted output, and $y(k)$, process output.

where $\hat{y}$ is the predicted process output, w is the reference trajectory, and H_p is the prediction horizon or output horizon. The structure of an MPC is shown in Fig. 2.

The controller output sequence u_{opt} over the prediction horizon is obtained by minimisation of J with respect to u. As a result the future tracking error is minimised. If there is no model mismatch i.e. the model is identical to the process and there are no disturbances and constraints, the process will track the reference trajectory exactly on the sampling instants.

Model Predictive Control algorithm, consists of the following three steps.

i) Explicit use of a model to predict the process output along a future time horizon (Prediction Horizon).
ii) Calculation of a control sequence along a future time horizon (Control Horizon), to optimise a performance index.
iii) A receding horizon strategy so that at each instant the horizon is moved towards the future, which involves the application of the first control signal of the sequence calculated at each step. The strategy is illustrated as shown in Fig. 3.

The selection of MPC to control an AUV is attributed to several factors. Some of them are listed below.

- The concept is equally applicable to single-input, single-output (SISO) as well as multi-input, multi-output systems (MIMO).
- MPC can be applied to linear and nonlinear systems.
- It can handle constraints in a systematic way during the controller design.
- The controller is designed at every sampling instant so disturbances can easily be dealt with.

In this paper, the optimisation of the performance index is done using GA, which is described in the next section.

2.1. Genetic Algorithms

GAs inspired by Darwinian theory, are powerful non-deterministic iterative search heuristics. GAs operate on a population consists of encoded strings, each string represents a solution. Crossover operator is used on these strings to obtain the new solutions, which inherits the good and bad properties of their parent solutions. Each solution has a fitness value, solutions having higher fitness values are most likely to survive for the next generation. Mutation operator is applied to produce new characteristics, which are not present in the parent solutions. The whole procedure is repeated until no further improvement is observed or run time exceeds to some threshold, (Sait and Youssef, 1999). The flowchart of a simple genetic algorithm is presented in Fig. 4 and the operation of the GA is explained as follows.

To start the optimization, GA use randomly produced initial solutions. This method is preferred when a priori knowledge about the problem is not available. After randomly generating the initial population of say N solutions, the GA use the three genetic operators to yield N new solutions at each iteration. In the selection operation, each solution of the current population is evaluated by it's fitness normally represented by the value of some objective function and individuals with higher fitness value are selected. Different selection methods such as roulette wheel selection and stochastic universal sampling can be used. The crossover operator works on pairs of selected solutions with certain crossover rate. The crossover rate is defined as the probability of applying crossover to a pair of selected solutions. There are many ways of defining this operator such as single point crossover, double point crossover, multi-point crossover etc. For example the single point crossover works on a binary string by determining a point randomly in the two strings and corresponding bits are swapped to generate two new solutions.

Mutation is a random alteration with small probability of the binary value of a string position. This operator prevents GA from being trapped in local minima. The fitness evaluation unit in GA acts as an interface between the GA and the optimization problem. Information generated by this unit about the quality of different solutions is used by the selection operation in the GA. Next the stopping criteria must be decided. This may be the case when there is no significant improvement in maximum fitness or the maximum allowable time (number of iterations) is passed. At the end of the algorithm, the best solution found so far is returned.

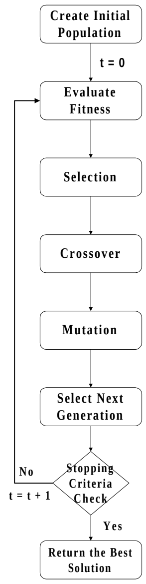

Fig. 4. Flowchart of a simple genetic algorithm

3. PROBLEM FORMULATION

In order to formulate the problem the following assumptions are made.

i) The AUV and target are assumed to be in the same plane.
ii) The target is assumed to be stationary, however, non-stationary targets can be easily dealt with and is area of active research.
iii) Navigation information is completely available to the guidance system.

The AUV-target engagement geometry is shown in Fig. 5. Both target and AUV are assumed to be point masses having co-ordinates (x_t,y_t) and (x_v,y_v) respectively. The guidance system generates the reference heading to be followed by the AUV which is simply the line of sight (LOS) angle λ formed between the AUV and the target given by Equation 2.

$$\lambda = \tan^{-1}\left(\frac{y_t - y_v}{x_t - x_v}\right) \tag{2}$$

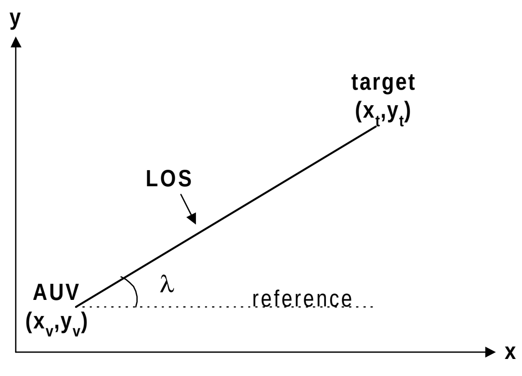

Fig. 5. AUV-target engagement geometry

The MPC is then responsible to direct the AUV towards the LOS. The following steps describe the operation of the MPC algorithm using GA. At any time step k

i) Evaluate process outputs using the process model.
ii) Use GA search to find the optimal control moves which optimise the cost function and satisfies process constraints. This can be accomplished as follows.
   (a) generate a set of random possible control moves. The control moves or population consists of real values which is reasonable in a real world environment.
   (b) find the corresponding process outputs for all possible control moves using the process models.
   (c) evaluate the fitness of each solution using the cost function and the process constraints.
   (d) apply the genetic operators (selection, crossover and mutation) to produce new generation of possible solutions.
   (e) repeat until predefined number of generations has reached and thus the optimal control moves are determined.
iii) Apply the optimal control moves generated in step 2 to the process.

4. SIMULATION RESULTS

The proposed MPC algorithm has been applied to an AUV test model supplied by the QinetiQ. The model relates the yaw angle to the rudder deflection. Dimensionally, the AUV is 7 meters long, 1 meter in diameter and has a displacement of 3600 kilograms. A full description of the equations of motion describing the dynamic behaviour of the vehicle in the lateral plane can be found in Craven, (1999). The model is derived from first principles i.e., using law of physics, which utilises theory of rigid body motion, kinematics and hydrodynamics. A simplified linear model is extracted using system identification from the non-linear MATLAB/Simulink simulation model provided. The identified model is of the form:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u} \tag{3}$$

where $\mathbf{A}$ and $\mathbf{B}$ are the state and input matrices respectively. More precisely the two-dimensional core state-space model is given by,

$$\begin{bmatrix} \dot{\psi} \\ \dot{r} \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} \psi \\ r \end{bmatrix} + \begin{bmatrix} e \\ f \end{bmatrix} u$$

where ψ is the yaw or heading angle in degrees, r is the yaw rate in degrees/sec and u the input signal to the canard. The model is discretised at a sampling rate of 0.1 samples/sec and converted to a transfer function model for the generalised predictive control algorithm.

The rudder actuator can move a maximum of 25^{o} to either left or right direction. The AUV initial position co-ordinates are (0,0) while the target is located at (200,0) giving the LOS angle λ equal to zero using Equation 2.

The MPC and GA parameters used in the simulation are provided in Table 1. The cost function used in this paper is given by

$$J = \sum_{i=1}^{H_p} e(k+i)^T Qe(k+i) + \sum_{j=1}^{H_c} \Delta u(k+j)^T R \Delta u(k+j) \tag{4}$$

subject to

$$u^l \le u(k+j) \le u^u$$

where the superscripts l and u represents the lower and upper bounds on the input moves respectively. R is the weight on the rate of change of control moves and Q is the weight on the prediction error

$$e(k) = \hat{y}(k) - w(k)$$

The second term in Equation 4 represents the penalty on the rate of change of control moves. This is augmented to prevent excessive movements of the rudder.

The AUV heading when the MPC is applied is depicted in Fig. 6, which clearly shows that the AUV is following the LOS closely. Fig. 7 presents the controller output, which are actually the rudder deflections needed to track the LOS and is within the constrained limits.

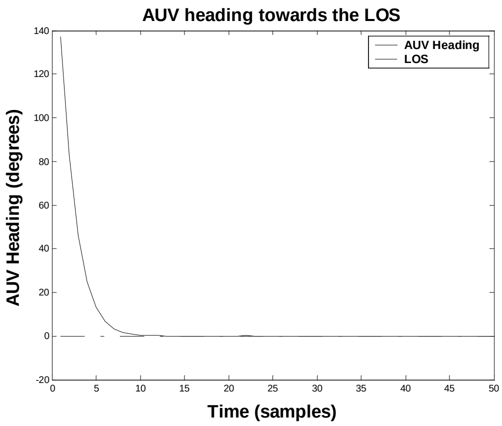

Fig. 6. AUV heading towards and tracking the LOS

Table 1 Simulation parameters for the GA and MPC

Parameter	Value
Prediction Horizon	10
Control Horizon	1
Population Size	50
Number of Generations	50
Mutation Probability	0.005
Crossover Probability	0.7
Q	1
R	0.1

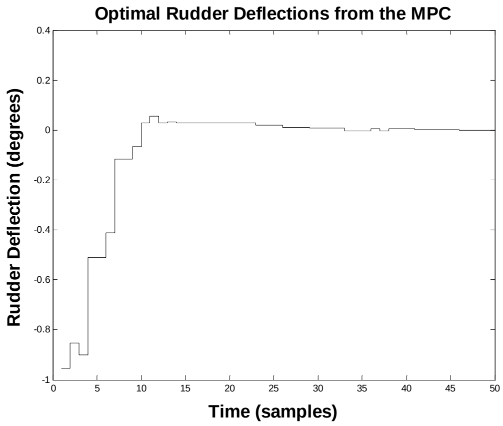

Fig. 7. Optimal rudder deflections generated by the model predictive controller

5. CONCLUSIONS

A new approach to control the yaw angle of an AUV using MPC has been demonstrated. The simple LOS guidance scheme is used to generate the reference heading. The results produced are for stationary targets and are quite encouraging as the actuator constraints are handled in an efficient way. Dealing non-stationary targets using the proposed algorithm is an area of active research. In addition, the technique is currently being employed on MIMO systems, however, this paper deals only with a SISO system.

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