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A SELF-ORGANISING FUZZY LOGIC AUTOPILOT FOR SMALL VESSELS

M. N. POLKINGHORNE

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A SELF-ORGANISING FUZZY LOGIC AUTOPILOT FOR SMALL VESSELS

by

MARTYN NEAL POLKINGHORNE

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ABSTRACT

Currently small vessels use autopilots based on the Proportional plus Integral plus Derivative (PID) algorithm which utilises fixed gain values. This type of autopilot is known to often cause performance difficulties, a survey is therefore carried out to identify the alternative autopilot methods that have been previously investigated. It is shown that to date, all published work in this area has been based on large ships, however, there are specific difficulties applicable to the small vessel which have therefore not been considered. After the recognition of artificial neural networks and fuzzy logic as being the two most suitable techniques for use in the development of a new, and adaptive, small vessel autopilot design, the basic concepts of both are reviewed and fuzzy logic identified as being the most suitable for this application.

The remainder of the work herein is concerned with the development of a fuzzy logic controller capable of a high level of performance in the two modes of course-keeping and course-changing. Both modes are integrated together by the use of non-linear fuzzy input windows. Improved performance is then obtained by using a non-linear fuzzy rulebase. Integral action is included by converting the fuzzy output window to an unorthodox design described by two hundred and one fuzzy singletons, and then by shifting the identified fuzzy sets to positive, or negative, in order that any steady-state error may be removed from the vessel's performance.

This design generated significant performance advantages when compared to the conventional PID autopilot. To develop further into an adaptive form of autopilot called the self-organising controller, the single rulebase was replaced by two enhancement matrices. These are novel features which are modified on-line by two corresponding performance indices. The magnitude of the learning was related to the observed performance of the vessel when expressed in terms of its heading error and rate of change of heading error.

The autopilot design is validated using both simulation, and full scale sea trials. From these tests it is demonstrated that when compared to the conventional PID controller, the self-organising controller significantly improved performance for both course-changing and course-keeping modes of operation. In addition, it has the capability to learn on-line and therefore to maintain performance when subjected to vessel dynamic or environmental disturbance alterations.

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AUTHORS DECLARATION

At no time during the registration for the degree of Doctor of Philosophy has the author been registered for any other University award.

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The following technical papers relate directly to the work described in this thesis and have been published, or are accepted for publication.

1. Polkinghorne M.N., Roberts G.N., Burns R.S. and Randolph W.A "A Review of Autopilots and Associated Control Simulation Techniques." SCS Multiconference, Copenhagen, 1991.

2. Polkinghorne M.N., Burns R.S. and Roberts G.N. "A Fuzzy Autopilot for Small Vessels." Proc. 2nd Int. Conference Modelling and Control of Marine Craft, Southampton, pp 349-362, 1992.

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4. Polkinghorne M.N. Burns R.S. and Roberts G.N. "The Implementation of a Fuzzy Logic Marine Autopilot." Proc. IEE Conference Control 94, Warwick, Vol. 2, pp 1572-1577, 1994.

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Signed:.................................

(M.N.POLKINGHORNE)

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CHAPTER 1. BACKGROUND AND STRUCTURE OF THESIS

1.1 INTRODUCTION

Over many centuries it has been the responsibility of the helmsman to guide maritime vessels through both rough seas and calm ones, and to be adept at carrying out the difficult manoeuvres required. This task can at times demand a high level of skill and judgement, whilst at others it is merely tedious and calls on continued concentration for long periods of time. To fully understand the range of activities undertaken by the helmsman it is useful to separate them into their differing modes of operation:

1. Course-Keeping.
2. Course-Changing.
3. Track-Keeping.
4. Berthing.
5. Collision Avoidance.
6. Navigation.
7. Roll reduction.

Since the 1920's there has been a gradual automation of the ship steering process, and due to advancements in technology the achievable performance and competence in the range of sea-keeping roles has increased. In recent years several attempts have been undertaken to develop systems capable of performing the tasks of track-keeping [1.1], automatic-berthing [1.2], collision-avoidance [1.3], navigation [1.4] and roll reduction [1.5] with a certain degree of success. It is only when considering the popularity and wide-spread application of the current autopilots for course-keeping/course-changing that the potential impact of automation in the marine environment becomes apparent.

1.2 SHIP AUTOPILOT DEVELOPMENT

As early as 1922 work by Sperry [1.6] described the main factors involved in automatic course-keeping as being ship characteristics, rudder effectiveness and vessel load. The magnitude of rudder movement required to counter yaw effects was shown to vary for different ships. Environmental disturbances, especially that of current, were highlighted and shown to greatly affect vessel's yaw performance.

In the same year Minorsky [1.7] analysed course-changing and proposed three sets of control equations which could solve the needs of early automatic steering. The first solution was that of "Position control of the angle of the rudder" and was the simplest form of control with the rudder movement set always to oppose that of the heading error. The scale of the proportional alteration was determined by a gain term. Minorsky demonstrated that a small gain produced a slow response whilst a large gain caused an undesirable oscillatory response. Considering that the amount of control effort was dictated by the rudder size, this system proved unreliable and was superseded by the second method called "Angular velocity control of the angle of rudder" where the rudder angle was varied proportionally to the instantaneous angular velocity of the heading error. The result was an improved level of performance with an increased damping effect, but unfortunately resulted in the formation of a steady state error. The third method was entitled "Angular acceleration control of the angle of rudder" and derived a rudder action proportional to the instantaneous value of the angular acceleration. The resulting performance proved similar to the second method.

By combining all three effects together, a specific set of steering characteristics was obtained. The combined controller could only cope with stochastic disturbances, e.g. a gust of wind, and not deterministic ones. This led Minorsky to the development of a new class of controller based on the "Rate of movement of the rudder". It was demonstrated that all of the original advantages were retained whilst the problem of deterministic disturbances was also overcome.

The main effect of the development of the control laws of Minorsky, and independently by Sperry, was to lay the basis for the simple course-keeping and course-changing operations of the early autopilots. By 1950 autopilot development led to the PID (Proportional plus Integral plus Derivative) controller which is currently widespread across the globe. Utilising the heading error, integral of heading error and rate of change of heading error, each term is multiplied by a gain factor prior to their summation:

$$\delta_d = K_p e + K_d \dot{e} + K_i \int e \, dt \tag{1.1}$$

where:

K_p, K_d, K_i = Gain terms.

e = Heading error.

δ_d. = Desired rudder.

Each of the gain terms in a PID autopilot may be adjusted to allow a degree of tuning. By this means it is possible for the PID controller to provide a satisfactory level of control for both course-keeping and course-changing actions. Due to the large scale of autopilot manufacture, it has been discovered that individual autopilot tuning is not normally practical, being replaced instead by pre-set gain values that match a broad category of vessel. In reality, marine vessels are non-linear time-variant systems. For example, a change in speed may take the vessel from displacement to planning mode, or alternatively a fishing boat may take onboard a catch, in either case the characteristics of the vessel dynamics will alter and a corresponding change in controller action could therefore be required. Any individual autopilot tuning at the point of sale would appear to be of limited use since the range of settings demanded by any one particular vessel to meet all likely scenarios is too great.

In an effort to remedy this acknowledged problem with existing autopilots, some manufacturers [1.8] provide the user with a limited range of adjustable parameters, for example:

1. Rudder Action or Rudder Ratio (Proportional Control).
2. Automatic Permanent Helm or Trim (Integral Action).
3. Counter Rudder (Derivative Action).
4. Course Deadband (Course Zone within which no new control is applied).
5. Weather (Rudder Deadband).

By the introduction of nautical names for the control parameters, the mariner is more able to relate the adjustments being made to the performance of the vessel. It is clear that in the majority of cases the person attempting to tune the autopilot is unlikely to fully understanding the implications of their actions and the likelihood of the autopilot operating close to its optimum point is extremely low.

The difficulty in maintaining both course stability and performance levels with varying disturbance effects and vessel dynamics has been described. Consideration must also be given to the auxiliary ship characteristics of accuracy of course, economy of fuel, economy of down track time, minimisation of speed loss and minimisation of rudder activity. All of these factors are aggravated by the demanded rudder activity resulting from an incorrectly tuned autopilot. Since the rudder turns the ship by introducing drag at the stern, then as the rudder activity increases then so does the drag. In addition, drag is also caused by the relative position of the vessel's hull, the effects of which can be minimised by correct rudder action.. It is inevitable that any drag will reduce the vessel's forward velocity and therefore these unnecessary drag effects will cause an avoidable loss in speed. In many instances a poorly tuned autopilot will cause the ship to follow an oscillatory path. This effectively increases the distance covered to reach a specified destination, the time taken to arrive at that point and also the amount of fuel consumed [1.9]. In certain conditions poor autopilot performance is noticeable by the presence of mainly high frequency movements in the rudder action. Very often, due to the time constants of most ships, fast alterations in rudder position have little or no effect on the vessel's motion . This activity over a period of time exerts a considerable amount of wear on the entire rudder mechanism. In the particular case of vessels under sail, the power available to supply rudder movement is restricted by battery capacity and therefore any unnecessary drain on this power is extremely undesirable.

In this thesis small marine vessels are considered those craft whose total length does not exceed thirty-five metres. Such vessels could be for commercial or leisure usage. Whilst this range of difficulties exists for all sizes of ships, it is in the case of the small vessel where they become most acute. Due to their limited draft and relatively short time constants in comparison to the tankers and freighters found on both the open sea and coastal waters across the world, the overall susceptibility of small vessels to incorrect controller action is of concern to current autopilot manufacturers. When external environmental disturbances are applied to the hull of a small vessel, the low inertia present creates little resistance to the induced heading change. The autopilot performance must therefore be particularly swift and decisive in this instance to counter any such effects by employing an opposing rudder condition, i.e. the autopilot must be working near its optimum performance level at all times. For large ships, the cost of the autopilot is a small proportion of the total cost of the ship, therefore such autopilots are often custom designed for a particular ship. In comparison, for the small vessel application, the cost of the autopilot is a high proportion of the total vessel cost. For this market, it is only practical to supply mass produced general autopilots which are capable of a wide range of operating performances. Given this, the PID controllers utilised for small vessels will only be capable of performing correctly when their gain values are set-up with suitable values.

After considering the problems associated with the conventional PID autopilots, it becomes apparent that there is a strong argument for the imposition of a new style of controller for this particular marine application. Whilst a range of modern control techniques have been applied to the problem of ship control in an effort to find a suitable successor to the PID autopilot, they have been directed at solving the specific problems that concern the masters of large ships by the implementation of robust controller designs. This thesis considers the unique problem of the automatic control of small vessels, the research being supported by Marinex Industries Ltd (trading under the name of Cetrek Ltd), who currently hold a large market share in the PID autopilot sales to small vessels, Marine Technology Directorate (EPSRC), the Royal Naval Engineering College (RNEC) Manadon and the University of Plymouth. This work was undertaken as part of a program of work entitled "Modelling and Control of Small Vessels", Grant Reference Number GR\G21162. In parallel to this study, an alternative investigation therefore focused on the mathematical modelling aspects of this application.

The presented arguments regarding PID autopilots hold true for both motor and sail craft, but it is the purpose of this thesis to dedicate its findings towards motor vessels. Not only is it essential to find a novel design of controller to outperform the conventional PID, but an element of intelligence must be integrated so that the on-line control is independent of the mariner and therefore both more simple, and economical, to use. Such a controller would also be capable of offering a performance level far closer to the optimum operating point than anything currently available.

Clearly, the ultimate objective of the new design will be an autopilot which has the ability to match, or improve upon, the performance of the conventional PID controller when subjected to a similar set of conditions. Controller inputs and performance level achieved will be measured in terms of the heading error and rate of change in heading error of the vessel. When it becomes apparent that these performance levels are unsatisfactory, the new autopilot must be capable of independent on-line adjustments so that improved performance may be obtained. In practice, the defined task is complicated by the need to relate performance now to past controller activity before correct modification is possible. Such a control strategy would allow for both incorrect autopilot tuning, and for alterations in vessel dynamics, e.g. changes in velocity or mass loading, or environmental conditions, e.g. typically in wind, waves or current.

The cost of an autopilot for a large ship is a small proportion of the total cost of the ship, therefore such autopilots are often custom designed for a particular ship, or type of ship. In contrast, the cost of an autopilot for a small vessel is a high proportion of the total vessel cost. It is only practical to supply this market with mass produced general autopilots which are capable of a wide range of operating performances depending on the controller settings. Development of this new autopilot design could therefore generate a market lead for the associated manufacturer, and consequently an increased market share. The important commercial implications of a successful design of autopilot are therefore recognised. Consideration is therefore given to ensure that the final design interfaces with existing complimentary software and works within the physical restrictions imposed by the current hardware utilised by Cetrek Ltd.

1.3 ORGANISATION OF THESIS

The contents of the following Chapters in this thesis are summarised below. The order of these Chapters was mainly organised to reflect the progression of the work as the intelligent autopilot design was taken from conception, through detailed design, to performance validation using full scale sea trials. The exceptions to this are Chapters 5 and 6 which were developed in parallel due to the close interaction between their respective elements. The relative positioning of these Chapters within this thesis is therefore to assist the understanding of their content.

Chapter 2: The Physical Autopilot System: Requirements, Restrictions and Modern Solutions

This Chapter describes the two required modes of autopilot operation, these being course-keeping and course-changing, and defines the level of performance expected from a small vessel autopilot. Previous work to analysis the vessel's response, employing a cost function approach, is also outlined. An attempt is undertaken to identify the major differences between the autopilot control of small and large ships. Within this framework it is also possible to specify both the criteria by which a satisfactory level of performance will be assessed, and also the limits of the operating envelope in which a small vessel autopilot must operate.

A review is subsequently undertaken of the modern control solutions applied to the field of automated ship control. Where relevant, inferences are drawn from this work which as all been dedicated to the large ship application.

Chapter 3: The Artificial Neural Network Solution: Principles and Implications

This Chapter considers the simplified biological neuron, and the historical development of artificial neuron. The fundamental strategy by which artificial neural networks operate in described, and the basic types of possible network learning discussed. Implications for control applications are presented, together with the potential for using artificial neural networks as a small vessel autopilot. The possible structure of a neural autopilot is proposed, and limitations, in respect of this application, are identified. Further extension of these ideas for intelligent control is considered.

Chapter 4: The Fuzzy Logic Solution: Principles and Implications

In a similar manner to Chapter 3, Chapter 4 describes the historical development of fuzzy controllers and the principle laws of fuzzy logic. By combining elemental fuzzy components together, a control strategy may be formed which is then discussed in relation to the small vessel autopilot application. The basic form of a fuzzy logic autopilot is therefore proposed which includes description of both the input, and output, defuzzification methods employed. As an extension to these ideas, the potential for advancing this type of fuzzy controller into an intelligent version is considered.

Chapter 5: Detailed Design of the Fuzzy Logic Foundation Autopilot

Whilst the general principles of a fuzzy logic autopilot are described in Chapter 4, in order to meet the specific performance requirements developed in Chapter 2, considerable original work was necessary to generate the fuzzy logic foundation autopilot onto which the intelligence could be subsequently added. A new autopilot design, using non-linear windows to fuzzify the inputs of heading error and rate of change of heading error, is proposed. This autopilot design enables the inclusion of both course-keeping and course-changing modes without extending the data requirements necessary to describe the shape and content of the windows themselves.

The autopilot is developed to emulate the conventional PID controller to prove the operational ability of the fuzzy mechanism. The third input variable, trim, is included in the autopilot by employing a new technique. To facilitate this action, the conventional fuzzy output window is replaced by an unorthodox design utilising fuzzy singletons.

Chapter 6: Extension of the FLC Design for Self-Organising Operation

Building on the foundation fuzzy logic autopilot developed in Chapter 6, the elementary principles of self-organising control are utilised, with a unique emphasis, to create a novel autopilot with the capability of a original style of on-line learning. Having established credibility in the methodology being utilised, the fuzzy autopilot is then modified by a new concept; i.e. replacement of the conventional rulebase with two non-linear enhancement matrices, one for each of the rudder ratio and counter rudder gains.

The self-organising structure developed, also applies to both rudder ratio and counter rudder, and in order to comply with the requirements of the small vessel, offers a new perspective in its method of operation. The inclusion of a data storage mechanism and a modification routine are discussed in conjunction with the necessary time delay feature. Application dependant performance indices are therefore constructed for rudder ratio and counter rudder with specific over-rules being identified to control the learning process. In addition, to allow for any necessary on-line adjustments, an adaptive methodology is developed for the trim setting.

Chapter 7: Autopilot Validation

This Chapter describes the performance obtained from the new design of autopilot in a range of studies. The nature of the tests is outlined and the objectives and results discussed. Full scale sea trials were utilised when evaluating the advantages of the self-organising fuzzy logic controller. However, it remained necessary to test the autopilot on other vessels. Unfortunately since it was not practical to use any alternative full scale vessels, a simulated set of results are presented based upon three different small vessel models. The conventional PID autopilot was used as a bench mark by which all the results could be validated when operating in the same environmental and dynamic conditions. Results are presented for both course-keeping and course-changing modes of operation. Details of the test vessel and a calculation of its time constant are included.

Chapter 8: Conclusions and Recommendations

Conclusions to this study are given in Chapter 8 regarding the successful operation of the self-organising principles when applied to the fuzzy logic controller designed for this small marine vessel application. Each of the important new design features of both the foundation, and of the self-organising, fuzzy logic autopilots are reviewed, with emphasis placed on how this new design resolves the difficulties previously associated with control of small vessels.

Aspects, such as the mariner's safety, skill and experience, are discussed in respect of both the current level of small vessel automation, and in view of likely future developments. This Chapter therefore draws on the experience gained from this research to identify the future requirements for intelligent small vessel control and our current potential for achieving them.

Appendix A - Further Details of the Conventional PID Test Autopilot

As with any design changes, the resulting controller must interface correctly with the existing system components in which it will eventually be embedded. The new design must therefore work within the same operational restrictions as its predecessor. A description is therefore given in Appendix A of the relevant design restrictions thus imposed.

Appendix B - Validation of the Foundation FLC Methodology

Appendix B contains the test results for the foundation fuzzy logic controller developed in Chapter 5. By comparing the output results, for given input conditions, against the conventional PID controller, the FLC's methodology may be validated at the design stage. The two sets of results demonstrate, as expected, that the FLC can be designed to operate in an extremely similar manner to the conventional PID autopilot. It is therefore concluded that the working methodology of the FLC is correct, and that the internal resolutions utilised are acceptable.

Appendix C - Publications

A list of the work published as a result of the study is given in Appendix C. Following this is a full transcript of each paper.

1.4 REFERENCES

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1.10. Procyk T.J., and Mamdani E.H. "A Linguistic Self-Organising Controller." Automatica, Vol. 15, pp 15-30, 1979.

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CHAPTER 2. THE PHYSICAL AUTOPILOT SYSTEM: REQUIREMENTS, RESTRICTIONS AND MODERN SOLUTIONS

2.1 INTRODUCTION

Before any new design of autopilot may be initiated, it is a pre-requisite that a detailed understanding is obtained of the conventional PID controller currently in use. The PID strategy utilised is part of an overall instrument system which can incorporate many auxiliary features including satellite position and navigation facilities, together with wind, velocity and water depth information. The total system must therefore comply to rigid rules regarding its general operating features if the entire network of facilities is to function correctly.

There are many practical issues, e.g. sample time, input/output resolutions and the range available input data, which must be considered before the new design of autopilot may be accepted for implementation. The potential problem areas, and hardware restrictions, require investigation so that any necessary trade-offs can be identified. It is also important to establish when the PID autopilot is expected to be operating, i.e. the conditions and the modes of operation. In both cases a limited amount of quantification can establish the expected limitations of the operating envelope to be investigated.

2.2 MODES OF AUTOPILOT OPERATION

There are two modes of operation which this type of small vessel autopilot would be expected to perform, these are named course-keeping and course-changing. Both modes are significantly different and must therefore be defined independently.

2.2.1 COURSE-KEEPING

The desired heading required by the mariner can be entered into the autopilot as an input. The course-keeping mode of operation then attempts to minimise the deviation from this desired heading by activating the rudder in a controlled manner. This deviation is called the heading error and is defined in equation 2.1.

$$\text{Heading Error} = \text{Actual Heading} - \text{Desired Heading} \tag{2.1}$$

The amount of effort required from the rudder to maintain a specified course is dependant upon boat characteristics, e.g. size/number of rudders, mass loading of the vessel (hence the water displacement), water depth and forward velocity, together with the environmental conditions of wind, waves, tide and current. Since the most obvious of the environmental factors is the effect due to wave action, it is important to be able to quantify acceptable and unacceptable operating conditions.

The state of the sea can be described in terms of sea-state codes which are numbered between 0 (calm) and 9 (phenomenal). Definitions for each sea-state code are given in Table 2.1. In each case the code represents a significant wave height (swh) [2.1] which is defined as the average highest one third of waves [2.2].

Similarly, a mean wind speed has been associated to each code rating to provide an indication of the possible disturbance that may be wind related (Table 2.2).

As a general rule, small vessels would not be expected to be at sea, under autopilot control in greater than a sea-state 5 [2.3]. Since sea-state codes 0 to 2 are variations of calm seas, the main situation when the autopilot is required to achieve its best performance is for sea-state codes 3 to 5.

Sea-state Code	Significant Wave Height (m)
0	0.00
1	0.05
2	0.30
3	0.88
4	1.88
5	3.25
6	5.00
7	7.50
8	11.50
9	>14.00

TABLE 2.1 SEA-STATE CODE DEFINITIONS

Sea-State Code	Mean Wind Speed (ms^{-1})
0	0.00
1	1.51
2	3.70
3	6.34
4	9.25
5	14.75
6	15.11
7	18.50
8	22.91
9	>23.00

TABLE 2.2 WIND SPEED ASSOCIATIONS

The superstructure above the waterline on small marine vessels is far smaller than that on a large ship, thus the wind effects could be perceived to be minimal. In practice small vessels are generally light and have little draft, their resistance to these induced wind effects is therefore significantly reduced.

The problem, particularly during course-keeping, is therefore to determine the correct controller settings. In good conditions, sea-state 0 to 3, only a small proportional gain is required to correct any course deviation. In the conventional autopilot the proportional gain is called rudder ratio (RR). High rudder ratio in this instance would cause the vessel to over-react and overshoot the set course. The vessel would therefore follow an oscillatory down track course, wasting time and fuel. The lifetime of the rudder may also be shortened due of the subsequent high rudder activity. However, should a low rudder ratio setting be used, and then rough seas encountered, the vessel will respond very slowly to any heading errors, and should the rudder ratio be too low, then insufficient control effort would be generated, and the vessel would drift further and further off course.

A derivative gain, called counter rudder (CR), may be employed to prevent overshoot resulting from high RR gain settings. However, it is likely that large counter rudder and small rudder ratio will cause the creation of a constant heading error which cannot be overcome. A similar effect is often introduced by the deterministic disturbances associated particularly with wind, tide and current. To overcome this the integral gain, called trim, can be tuned so that any constant heading errors are gradually reduced. This type of action operates most effectively when activated slowly, i.e. over a reasonably long period of time in comparison to the sample time of the controller and the significant time constants of the vessel. When the trim value is too small the steady-state error will not be overcome sufficiently quickly for correct course-keeping. Conversely, when the setting is two high an oscillatory performance can again be induced.

A further consideration, which needs to be taken into account, is the rudder action. As the RR gain value increases and the course deviation is reduced more rapidly, the associated high rudder activity will cause unnecessary wear and use excessive power. Potentially avoidable resistance to the vessels forward velocity will also be induced. These negative velocity implications were initially identified by Nomoto and Motoyama [2.4] in 1966. With application to both a tanker, and a cargo vessel, the estimated power loss, due to "the inertial resistance induced by yawing and the resistive component of rudder force", ranged from 2% for a reasonably adjusted autopilot, to as much as 20% in the most exceptionally poor case. The need for a 'tight' course, and correct autopilot settings, is therefore obvious, but must also be balanced by the practicalities of the vessel and the mechanisms involved.

It was established in section 2.1, that for correct autopilot tuning, it is a necessary to take into account external factors such as forward speed, water depth and weather conditions. Whilst on large ships, the relevant sensors are present to measure many of these parameters, when considering the small vessel application, it is rare that such devices will be installed due to their relative cost. In practice, the only data likely to be available would be wind speed/direction and forward velocity. However, since the installation of even these sensors may be considered rare on a small vessel, then any new design of autopilot must not be reliant upon the provision of such data if it is to be considered as a realistic replacement for the conventional PID autopilot currently in use.

Given the complications of tuning PID controllers, the small vessel mariner, who is not an expert in control, and the lack of available data to base such adjustments on, the settings employed are often not ideal and can therefore lead to far from optimal control.

2.2.2 THE USE OF COST FUNCTIONS DURING COURSE-KEEPING

A trade-off is necessary between minimising the heading error and the rudder activity. Koyama [2.5] proposed, following a study of work associated with a cargo ship, that this could be achieved by attempting to minimise a continuously monitored cost function which incorporated both heading error and rudder activity terms, equation 2.2:

$$J = \bar{e}^2 + \lambda\bar{\delta}^2 \tag{2.2}$$

where:

J = Cost function to be minimised.

$\bar{e}^2$ = mean square of heading error.

$\bar{\delta}^2$ = mean square of rudder angle.

λ = weighting function.

The value of the term λ, which was considered by Koyama to be in the range 8 to 10, proved to be dependant upon the type of vessel, and dictated the relationship between heading error and rudder activity described by the cost function J. Having established the most suitable value for λ, the PID gains could be tuned to obtain the desired autopilot performance. With any subsequent change in environmental conditions, these gain settings would no longer be applicable and the iterative process would need to be repeated. Work by Norrbin [2.6], concluded that a similar cost function would be sufficient if utilised with a significantly smaller λ value equating to approximately 0.2 for an equivalent type of ship [2.7]. It is clear that the Koyama value of λ. is much more punitive towards the rudder activity when compared to Norrbin's and therefore ignores vessel oscillations which are small, i.e. oscillations over which the rudder is unlikely to be able to exert control on a large vessel.

In the case of a following sea, it is possible that the added resistance effects generated by the vessel, or rudder, may provide a positive propulsion force which would then assist in the reduction of the vessel's fuel consumption and down-track speed [2.7]. Further consideration was again given to the implementation of cost functions, during course-keeping, this time by Motora and Koyama [2.8] who refined equation 2.2 to that given in equation 2.3, and utilised a value of between 4 and 8.

$$J = \frac{1}{t}\int_0^t (\bar{e}^2 + \lambda\bar{\delta}^2)dt \tag{2.3}$$

In a subsequent study, Astrom *et al* [2.9] determined that for the Bore 1 type vessel, with $\lambda = 0.1$ there was a fast response, but impossible rudder angles were demanded. Conversely for $\lambda = 10$, the response obtained proved sluggish, with the resultant steering quality being very poor.

Additional work has also been carried in this area in a variety of studies including work by van Amerongen and van Nauta Lemke [2.10], and Broome *et al* [2.11 and 2.12]. However, irrespective of the vessel under consideration, the desired relationship between heading error (possibly also the rate of change of heading error) and the rudder activity remains fundamental to the ability of any cost function to successfully formulate an acceptable assessment of an autopilot's performance. Further to this, Clarke [2.13] determined that minimising the heading error could be equated to a reduction in the down-track path length, thereby improving the heading response. Conversely, minimising rudder activity, and/or the rate of change of heading error, resulted in a reduction of the increased resistance, and therefore subsequent reductions in fuel usage, loss in forward velocity and rudder wear.

Clarke also directly related cost function magnitude to fuel saving, equation 2.4, and determined that the scale of the fuel saving, when applied to a large ship, could be a large percentage of the total fuel cost. Given the huge fuel bills associated with such vessels, the amount saved could therefore become quite considerable.

$$\text{Fuel Saving} = a\overline{e^2} + b\overline{\dot{e}^2} + c\overline{\delta^2} \tag{2.4}$$

where, in addition to consideration of the type of vessel, a, b and c are weighting factors dependant upon type of propeller, engine control system and rudder geometry.

The studies cited above have all considered applications to large ships, however the basis of the cost function approach for identifying autopilot performance may also be related to the small vessel application. In the small vessel case, the balance between heading error, rate of change of heading error and rudder activity is significantly different. Due to the relatively fast dynamic characteristics of small vessels, the rudder is normally fully capable of controlling even small heading movements, assuming that sufficient RR gain is being utilised. The large vessel requirement to put the cost function emphasis onto the rudder in this situation, therefore needs to be modified. By employing a very small value of λ, minimisation would be concentrated on the heading error, with the rudder activity being regarded as less important. Considering the special needs of a small vessel, e.g. limited size of rudder and power supply, clearly there is a need for a compromise λ value to ensure that rudder activity does not escalate, however this value could be expected to be of relatively small magnitude. In addition to the relationship with the heading error, the rudder activity may also be related to the rate of change of heading error. Since it is heading error and rate of change of heading error which causes the rudder to become activated, it should be possible to minimise rudder activity by minimising these two terms only. With the small vessel, this technique would be more applicable than with a large ship, due to the low inertia of the small vessel. Previous work by Eda [2.14] concluded that the frequency of hull and rudder motions are not similar for large ships. However, as the size of the vessel is reduced, then these frequencies begin to coincide. It may therefore be inferred that, for the small vessel, the frequency of the hull movement may be considered as representative of the frequency of the rudder movement.

On a typical small vessel, measurement of the hull movement is not an available, neither is measurement of the frequency of rudder motion. However an estimation of this frequency may be obtained from the rate of change of heading error data. When this rate term is low, then the vessel, and thus the rudder, may be considered to operating in a desirable manner. Conversely, when this rate term is high, then either the frequency is low, but with a large amplitude, or the frequency is high. Both of these conditions may be considered as being undesirable when taken in isolation. In practice the true performance of both vessel, and rudder, must be considered together when formulating a judgement concerning the overall level of performance obtained. Any rate of change of heading error information obtained by the autopilot must therefore be seen to have direct relevance to the current vessel performance, and consequently to the demanded rudder action. The only available method of assessing the performance of the small vessel is thus by the analysis of both the heading error and rate of change of heading error.

2.2.3 COURSE-CHANGING

When a new value for desired course is entered into the autopilot system, the autopilot generates the rudder demand necessary to move the vessel onto this new heading. This mode of operation is called course-changing and is applied for all heading changes in the range ±180°. At a simplistic level the vessel must be "brought-around" as quickly as possible until the actual heading is nearing the desired course. At this time, allowance must be made to prevent any possible overshooting of the desired course, and the control required must therefore be much more delicate. Irrespective of later characteristics within the course-change, it is important, for reasons of safety, that the start of the course-change is clearly defined so that other vessels are immediately aware of the intention to manoeuvre.

Overshoots are particularly undesirable because, dependant upon their magnitude, significant corrective rudder action may be required. As with course-keeping, this additional rudder activity generates unnecessary rudder wear, increased drag effects and subsequently a loss in forward velocity. Any corrected manoeuvre by the vessel will considerably reduce the comfort of passengers, or cargo, and may confuse other shipping which may cause a collision to occur. Whilst with large ships these factors must be taken into account when still considerably off course, in the case of small vessels, which respond very swiftly to new control demands, counter rudder may only need to be applied when the vessel is less than 10° off the new desired course.

Since the vessel, during course changing, is passing through various headings, there is no requirement for integral action to alter during this period, as the direction of the prevailing weather conditions, in relation to the vessel, will be changing. It is inherent in the nature of the integral action that the steady-state error over a period of time is utilised to calculate the constant rudder off-set required to maintain the desired heading. As the desired heading is altered, then any previous steady-state error will cease to be relevant to the new vessel heading, therefore any calculated rudder off-set will also be incorrect. and may cause a detrimental effect on the vessel's performance.

In most current autopilots, the settings for rudder ratio and counter rudder used for course-changing and course-keeping are identical. The difficulties encountered by combining these two mode, without a subsequent variation in gain values, was discussed by Oldenburg [2.15], who identified that a course-keeping autopilot, when applied to course-changes, would overshoot the desired heading with a subsequent loss of speed. However, when a course-changing autopilot was applied to course-keeping, it would not be able to identify when to end a turn and stabilise on a straight course, and that the ability to maintain that straight course would be rather poor.

For a small vessel, it is up to the mariner to attempt to tune these values whilst in the course-keeping mode, when the visible performance of the vessel is more obvious.

The result is that during the course-changing mode of operation, it is unlikely that the RR and CR gain settings will have been determined to obtain optimal performance, thus having a detrimental effect on the speed and accuracy of the course-changing manoeuvre. Typically the relatively low gains of course-keeping, when used for course-changing slow the response time considerably.

2.3 CONVENTIONAL PID TEST AUTOPILOT

Before considering the design of a new autopilot, it is a pre-requisite that an understanding is obtained of the conventional PID controller's operation. The PID autopilot, used in this study as a benchmark for subsequent comparisons to any new autopilot design, is from the C-net range produced by Cetrek Ltd of Poole, UK..

Further details of the PID test autopilot, which are specific to this particular hardware set-up, and therefore must be given consideration when implementing any new autopilot design, are described in Appendix A.

2.4 MODERN AUTOPILOT ALTERNATIVES

Recognition of the problems associated with the implementation of conventional PID algorithms as a means of autopilot control has long since been established. As various design enhancements have been incorporated to the basic design, the required hardware necessary to operate the PID algorithm has advanced from the operational amplifiers utilised for early applications, as discussed by Wesner [2.16], to the high technology microprocessor based systems found today, e.g. the PID test autopilot. By advancing the technology to cope with the improved PID controller's requirements, and due to the reduction in the costs associated with digital hardware, scope has been introduced for the expansion to alternative methods of control which would not have been possible using the previous analogue systems.

The initial adaptive style of autopilot design was based on the optimisation of a defined cost function, using data from external sensors to derive internal controller modifications [2.10, 2.11, 2.15 and 2.17]. Subsequently, a new type of controller emerged which utilised modern control techniques based upon the mathematical models of ship's steering dynamics.

As a result, there have been two significant applications of adaptive autopilots using a model reference technique. The first application [2.18] utilised a sensitivity approach, this may be considered as synonymous with a continuos hill climbing method, whereby model dynamics were derived from the data obtained from a specific training vessel. Both the model, and the actual system, were designed with identical configurations, but in the case of the model, the input derivation was based on a non-linear function. Adaption was controlled by a quadratic cost function which included a sensitivity coefficient generated by the model. Dependant upon the magnitude of the resulting cost function, a term in the actual system was adjusted so that cost function minimisation could be obtained. The major disadvantage found with the sensitivity model approach, was that it could not be considered to be stable under all circumstances [2.19].

In addition, later work by van Amerongen *et al* [2.19 to 2.21] followed a Liapunov (second method) approach, but concluded [2.20] that without noise, the Liapunov design adapted more quickly, however, in the presence of noise, the sensitivity approach provided the more significant improvement in performance. The variation between the success of the two methods was therefore minimal.

Initial results were inadequate due to the high noise associated with certain sea state conditions, and subsequently resulted in high frequency rudder activity. By the implementation of a low-pass filter, the problems associated with noise were overcome. Van Amerongen [2.21] found that after trials on a 170m long vessel, use of the model reference technique was successful, generating a 1% speed increase and 5% power saving (hence reduced fuel usage).

When compared to the optimal state feedback controller, the optimal method provided improved performance on long voyages where fuel could be economised, and sufficient time was available for the transfer function identification to be completed. However, the model reference system generated improved control, particularly in coastal waters where the behaviour of the vessel is more likely to vary. Kallstrom [2.22] argued that the course-keeping performance of the model reference controller was poor because the disturbance effects were not taken into account explicitly, and instead proposed a significant alternative autopilot [2.23] using a self-tuning method derived from the work originally undertaken by Astrom and Wittenmark [2.24] which was based on minimum variance control and least squares estimation. The controller was designed to adapt to variations in ship velocity by employing velocity scheduling, thus enhancing the speed of adaption. With the addition of a Kalman filter, the quality of the adaption was significantly improved. For this tanker application, drag improvements of 2.7% were reported for the self-tuning controller, when compared to a well-tuned PID controller. However, the two major limitations of the basic algorithm were the absence of both set point following, and control action penalty. These two aspects are essential if heading error and rudder activity are to be minimised successfully. Alternative autopilot applications have subsequently been investigated which further develop the algorithm [2.25 to 2.27], the findings of which concluded that self-tuning control can be suitable for both course-keeping and course-changing modes of operation. In the case of Mort [2.27], the results compared very favourably with those of an optimal state feedback controller (with complete knowledge of parameters), and in tests proved capable of monitoring even slowly varying parameters with relative success.

Van Amerongen has also applied the principles of fuzzy logic to elementary autopilot control of a 45m naval training vessel [2.28]. Using two different input window designs, each of five sets, and a fixed rulebase, it was concluded that a separate "close-by "control was required during the mode of course-keeping to maintain performance. Subsequent rudder control was achieved in "gusts". This study concluded that when free of noise, the fuzzy autopilot proved less susceptible to parameter variations when compared to the PID controller. Following the addition of noise, the fuzzy version demonstrated a significantly enhanced performance with fewer rudder calls.

Garcia [2.29] employed an adaptive fuzzy logic controller which utilised gain scheduling for both vessel mass and forward velocity in such a manner that as the forward velocity increased, then the gain value decreased. Conversely, when the mass increased, then the gain value also increased.. When applied to a cargo liner type of vessel, it was concluded that this method proved effective when varying both parameters. However, this form of adaption is relatively crude when considered in the small vessel context, and a more sophisticated means of adaption is required if the more subtle aspects of the small vessel characteristics are to be taken into account.

In a more recent study, Sutton and Jess [2.30] employed an intelligent version called the self-organising controller for a warship application. The rulebase was initially empty of rules, subsequent rule adaption was then carried out by interrogating a performance index to identify the magnitude of the changes required. The rule values were then built up by exciting the autopilot through a repetitive series of course-changing manoeuvres until a satisfactory level of control was obtained. Of particular importance is that by utilising this approach, the controller's dependency upon an accurate ship model was decreased, whilst a pre-determined level of performance was maintained. When compared directly to Mort's self-tuning controller, and applied to the same warship simulation model, the self-organising controller exhibited an improved course-changing response, but required a longer learning time.

A further study [2.31], which also includes input from van Amerongen, considered the application of a neural network autopilot to ship control. A supervised network was trained using data from a PD controller. Similarly, an additional network, utilising reinforced learning based upon a cost function, was also employed. The supervised learning network proved capable of learning the presented data, and learning the inclusion of non-linearities, e.g. deadbands, with a high degree of success. In the case of the reinforced learning network, on-line learning was undertaken at 50 second intervals. Whilst learning was achieved, the level of performance obtained proved less conclusive when subjected to noise due to environmental disturbance effects. More recently further work at an elementary level has also been undertaken by Sen *et al* [2.32].

Another alternative autopilot design has been the implementation of $H\infty$ [2.33 and 2.34]. $H\infty$ is a robust, frequency based, control technique which has been applied to the large ship application, a roll on/roll off passenger ferry, for both course-keeping and course-changing modes of operation. The resulting performance demonstrated that the $H\infty$ autopilot design was insensitive to model uncertainty, with a quick , and effective course-change, generating only minimal overshoot. Whilst the robustness of this type of controller is recognised, there is no obvious means of extension to any form of adaption. In addition to any robust qualities, for the small vessel application it is a pre-requisite that any new autopilot design must include an element of on-line learning in order that the required level of performance may be obtained, given the wide range of possible vessel types and operating conditions. Robustness alone can not be considered to be sufficient development from the conventional PID controller to achieve the required market lead for the given manufacturer.

It is clear that a range of techniques have been applied to the problem of ship autopilot control over recent years. However, in every case the application has been for large shipping. Consequently no consideration has been given to the difficulties of small vessels which are distinctly unique and therefore require the design of a new, dedicated autopilot if the full performance potential of the small vessel is to be fulfilled. To satisfy these small vessel requirements, the new design of controller must be more than just robust. It is therefore essential that the new autopilot is capable of on-line adjustment using only the minimal knowledge concerning the vessel dynamics. The adaptive controllers developed for large ships have demonstrated the need for precise vessel details. However, in the applications of both the neural network and fuzzy logic autopilots, it is apparent that the addition of a form of intelligence was possible which was less vessel specific. Given that any small vessel autopilot will ultimately be employed on a variety of vessel types, such a form of learning is an essential element of any potential new design. A further investigation was therefore undertaken to assess the capabilities of both the neural network and fuzzy logic techniques to the small vessel autopilot application.

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CHAPTER 3.THE ARTIFICIAL NEURAL NETWORK SOLUTION: PRINCIPLES AND IMPLICATIONS

3.1 INTRODUCTION

Artificial Neural Networks (ANNs) have been developed to deal with complex learning problems and analysis procedures. The working philosophy behind ANNs is based on that of the human brain since it is a widely held belief that the brain is truly a masterpiece of biological engineering. Therefore, if we are attempting to reproduce the results of human operation in an automated format, then it is only logical to develop an interactive system that has a similar mode of computation. In practice the brain is far too complex to mimic satisfactorily, but the ANNs currently being utilised demonstrate certain characteristics of the brain and are expected to find an increasing range of applications in the next few years. In order that an improved understanding of ANNs is possible, sections 3.2 provides a brief overview of the principles involved in the biological operations performed by the brain.

3.2 OPERATION OF THE BIOLOGICAL NEURON

A study of the human brain, which weighs approximately 1.5 Kg [3.1], would show that it is constructed from a series of smaller modules called 'neurons'. Whilst the total number of biological neurons may exceed twelve thousand million [3.2], each individual one plays an important role in the overall functioning of the brain. The three principle types of neurons are sensory, motor and connector. Sensory neurons interface with functions external to the brain and therefore receive incoming data, e.g. from eyes or ears. When subjected to excitation these sense organs produce an impulse which is then passed to the sensory neuron. Motor neurons activate external functions when "fired", e.g. muscle control, and connector neurons feed signals from sensory to motor neurons. It is through the implementation of chains of these neurons that a human being is able to exhibit the characteristics regarded as memory, learning and thinking.

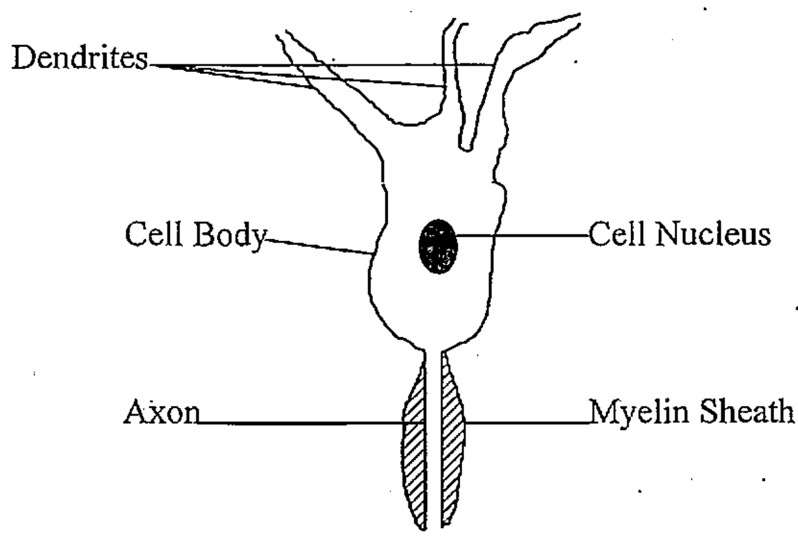

Figure 3.1 The Biological Layout of a Neuron

Each neuron consists of a soma from which extrude dendrites (inputs) and a single axon (output). Around the axon is a myelin sheath which provides an insulating effect and therefore generates an increased speed of conduction (Figure 3.1). Considering a large diameter axon with a myelin sheath the possible rate of conduction could be as high as 120 ms^{-1} [3.3], conversely for a small diameter axon without the effect of increased conductivity the rate of conduction could be as low as 1 ms^{-1}. Each neuron has a threshold of response and only when the input impulse is greater then this threshold will an output impulse be passed down the axon. The impulse itself is formed by each section of the axon depolarising and repolarising after a 1 ms delay. The depolarisation occurs as potassium ions (K) and sodium ions (Na) redistribute themselves on either side of the axon's membrane. No signal deterioration takes place along the length of the axon, but the rate of impulse fire is determined by the strength of the input stimulus. Subsequent to each output impulse fire there is a period of time called the absolute refractory period, which lasts approximately 1.5 ms during which no firing can take place. Following this delay there is an additional period when although firing can take place, the threshold is set higher than normal making only strong input impulses effective. The resultant firing rate for a weak stimulus may be as low as 25 impulses per second compared to 1000 impulses per second for a strong stimulus.

The axon in turn connects to many other neurons at a point called the synapse (Figure 3.2). When the impulse reaches the synaptic knob, the real operation of the neuron begins and is achieved through a chemical process using transmitter substances containing acetyl chlorine (Ach). The actual size of the synaptic gap is only approximately 20 nm [3.4]. Only when sufficient quantities if the transmitter substances have been released causing a strong enough impulse, will the next neuron be activated. However, this level may be achieved from the axon of one neuron or by the combination of smaller outputs from several neurons (summation). This type of operation occurs at excitary synapses, but in a similar manner inhibitory synapse exist to inhibit the operation of subsequent neurons.

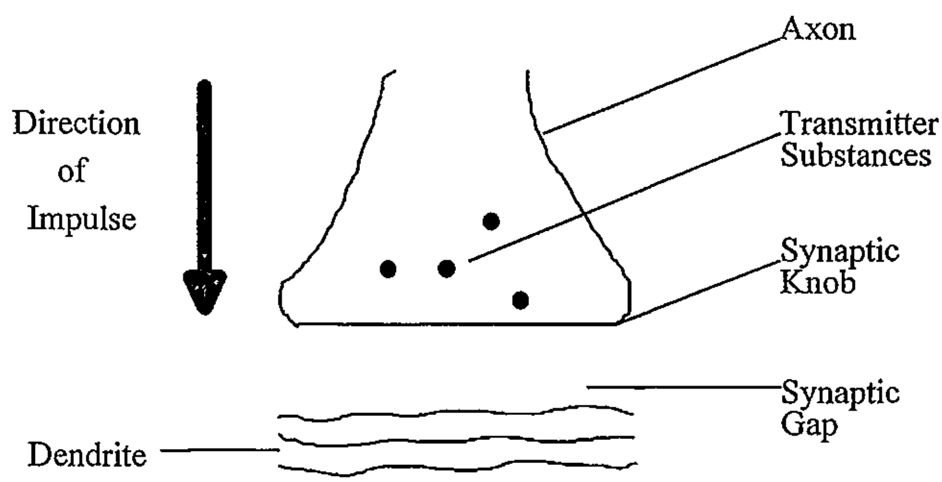

Figure 3.2 The Synaptic Layout

By biologically adjusting the efficiency of the synapse so that the pulse magnitude is manipulated in a controlled manner, the derived output of a series of neurons to a given input may be tuned so that the output itself becomes closer to a predetermined desired value. Since synapse efficiency is altered on a local level for the brain to learn new experiences, the distributed efficiencies on a global level, remain unaffected and thus recall of past experiences is retained. The brain has therefore developed a unique memory facility with a huge capacity for information retention whilst still being fully capable of updating to respond to new conditions.

3.3 A COMPUTATIONAL NEURON

The computational neuron is a simplistic but functional form of its biological counter-part (Figure 3.3), and therefore can be found in three distinct types, these being a sensory (input) neuron, a motor (output) neuron and a connector (hidden layer) neuron. In each case the basic function of the ANN is performed in an identical manner, but small operational changes occur in the case of the input and output neurons.

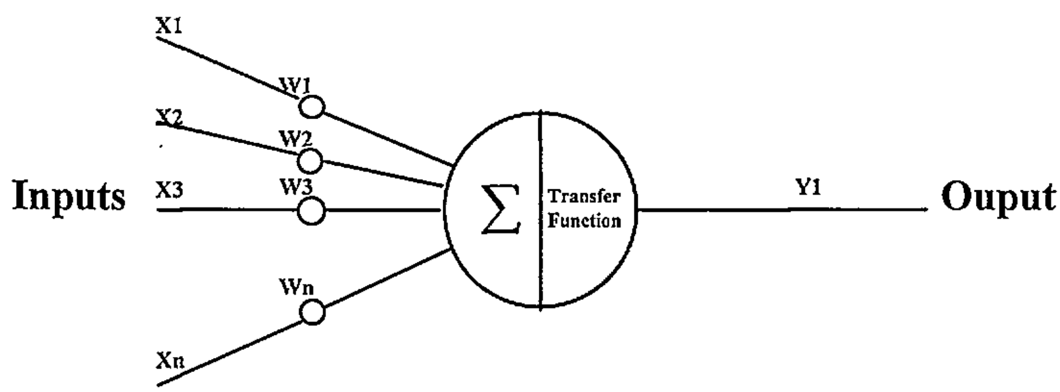

Figure 3.3 The Computational Neuron

In the case of the hidden layer neurons, each axon to dendrite connection is modelled by an input signal with a modifiable weight. By the adjustment of this weight the significance of the previous neuron outputs can be adjusted in the same manner as is possible with the synapse's efficiency. Using the biological summation approach [3.1], all of the inputs to a neuron are summed to obtain a total input (I) to that neuron (equation 3.1).

$$I_i^s = \sum_{j=1}^{n} x_j^{s-1} \cdot w_{j,i}^s \tag{3.1}$$

where:

I = total input to neuron.

s = layer in ANN of neuron.

i = identification of neuron in a specific layer.

j = identification of source neuron for the input.

x = magnitude of input to neuron.

w = weight associated with input.

A transfer function is utilised to model the threshold function. By the application of the total input of the neuron to the transfer function, the output from the neuron may be determined. The commonly used transfer functions are linear, bound linear, hard limiter, sigmoid or hyperbolic tangent functions. Which particular function is chosen is dependant upon the application and any imposed limitations. A bias term is added so that the transfer function for each neuron may be offset, this bias is classified as input 0 and is always set to a magnitude of 1. However, manipulation using a weight means that the offset is adjustable. Equation 3.1 can therefore be modified to incorporate the new input:

$$I_i^s = \sum_{j=0}^{n} x_j^{s-1} \cdot w_{j,i}^s \tag{3.2}$$

Whilst this is the true for most neurons in a network, in the case of the input neurons there is only one input line supplying data and no associated weight. In practice the total input for an input neuron is therefore the input itself. Conversely for the output neurons the single data output line must be calibrated so that the maximum and minimum outputs represent the values required by the receiving device. Having defined the nature of the individual artificial neuron it is possible to link them together to form a powerful and manipulative structure.

3.4 THE HISTORICAL DEVELOPMENT OF ANN'S

In 1943 McCulloch and Pitts [3.5] launched a great debate on the subject of ANN's with their paper proposing a simple model of a neuron. Using a binary output format, the total weighted input was computed and an output produced when the threshold had been exceeded. Hebb [3.6] in 1949, described details of a technique which became known as 'Hebbian Learning', i.e. connections between neurons are strengthened with increased activation, and in addition he introduced a learning algorithm for weights which assumed only positive activation levels and therefore was severely limited.

Rosenblatt [3.7] was investigating optical pattern recognition, and by 1957 proposed the 'perception': a single layer network of neurons which proved capable of learning both geometric and abstract patterns by utilising a 400 photocell grid to correspond to the light sensitive retina neurons. The linear nature of the perception was identified as a serious restriction [3.8] in its capabilities when presented with specific problems to solve, e.g., the Exclusive OR (XOR) function. This could be overcome by the introduction of additional layers of neurons giving a 'Multi-layer Perception' (MLP) but at this time there was no successful way of training the weight values to optimise such a network.

In a similar fashion to the perception, the 'Adaline' network [3.9] was developed which included bi-state inputs, and a bias input which remained at unity. The weighted summed input was then applied to a threshold capable of outputting -1 or +1. The weights were signed to achieve the desired network response, and a new learning algorithm was presented. This algorithm adjusted the weight values depending on the output error, which was derived by comparing the actual network output to a desired one for that particular set of inputs. As with the perception, the Adaline was capable of classifying linear patterns. The Adaline network was later developed into the Madaline (Multiple Adaline) which has subsequently proved successful in applications such as speech recognition, character recognition, weather prediction and adaptive control and led to the production of an adaptive filter used to reduce the echoes present on telephone lines.

Kohonen [3.10] and Anderson [3.11] were investigating similar areas on an independent basis in 1970, respectively calling their work "associative memory" and 'interactive memory'. Anderson utilised the Hebbian principle to develop a linear associator based on memory models for retrieval and recognition. He later developed the Brain-State-in-a-Box (BSB) where the box represents the saturation limits allowable for each neuron state. Kohonen favoured an approach called "competitive learning". Here each processing element competes to respond to a certain stimulus and the winner is then allowed to update itself so that it will respond in a stronger fashion every time that particular stimulus is represented. Later Hopfield [3.12] suggested a novel network where all neurons had a unique input but were connected to all others. These new networks required a large number of neurons but were capable of demonstrating improved learning characteristics.

The Sigmoid function of Grossberg in 1973 complemented the new learning algorithm called back-propagation which followed in the subsequent year from Werbos [3.13]. This new algorithm was not fully developed at that time, but was rediscovered simultaneously [3.14][3.15][3.16] and is now regarded as a highly powerful learning mechanism, allowing the MLP theories previously presented to be applied to a wide range of modern applications, including pattern recognition and control. It is also able to cope with the non-linear computation problems, such as the XOR function.

3.5 CONSIDERATION OF AN ANN AUTOPILOT

Whilst the use of ANNs for pattern recognition is widely applied. In the field of neural research, there is currently great debate concerning the applicability of ANN's to control problems. If a control situation is regarded with an "open mind" it can be seen to consist of a series of outputs for given inputs, i.e. this is in fact a classic pattern . Therefore there is no reasonable argument as to why a pattern recognition approach should not provide adequate control given that the complexities of the network are sufficient to cope with actual range of patterns presented. In an autopilot application the number of patterns possible is vast, and the relationship between them often non-linear. In addition, the high-speed with which

the patterns are presented to an autopilot, and the short sample times employed, means that the utilisation of an ANN for a small vessel autopilot is quite a demanding applicational test.

There are currently three main methods for determining the weights for an ANN, these being:

1. Supervised Learning - The network is presented with data (a teacher) which are representative of the range of input possibilities that the network is expected to encounter, together with the associated inputs\output(s).The weight values are then adjusted until the error between the actual output of the network and the expected output is minimised. This process therefore requires substantial amounts of suitable data for training, prior to implementation of the network.

2. Learning with a Critic - The network is allowed to adjust the weights in an on-line fashion dependant upon a predetermined critic or cost function . The weight values are then adjusted to minimise this cost function. This has the advantage in situations where teaching data is not available or when unexpected conditions are possible. The major disadvantage is that the ability of the network to learn is restricted to current experience and therefore any acquired knowledge of alternative operating requirements can be lost.

3. Unsupervised Learning - There is no requirement for previous system knowledge or critic development with an unsupervised network. The network algorithm must be capable of recognising any patterns present in the experienced inputs and therefore only local data is available to calculate internal weight adjustments. The required number of inputs for this type of learning is relatively high as are the time requirements for learning to be completed.

For this application the data requirements of the supervised learning method could be met by the extraction of the relevant variables, i.e. heading error, rate of change of heading error and desired rudder, from operational PID controllers. By combining the data from several optimally tuned PID autopilots into a single ANN, it is possible that an increase in performance across the operating envelope could be achieved.

3.5.1 Network Architecture

Utilising an ANN of the MLP format, i.e. one or more layers and several artificial neurons in each layer, it is necessary to specify the number and component type of each input and output required for network operation. Given the inputs applied to the conventional PID controller, and a pre-requisite that the PID performance should be matched or bettered, it would appear a natural selection that the network inputs should be identical to those of the PID, with the addition of a bias. It is recognised that the addition of extra inputs, e.g. velocity, wind speed/direction, would enhance the possible performance of the ANN. However, due to the hardware restrictions discussed in Appendix A, this is not possible.. As with the PID controller there is only one required network output, this being the desired rudder value. The probable network (Figure 3.4) may therefore be described as a four input and one output system. The inputs being heading error, rate of change of heading error, integral of heading error and bias, and the output being desired rudder.

The number of layers, and of neurons in each layer should be maintained at the minimum quantity capable of performing to a satisfactory level, to ensure that the controller remains as compact as possible for implementation.

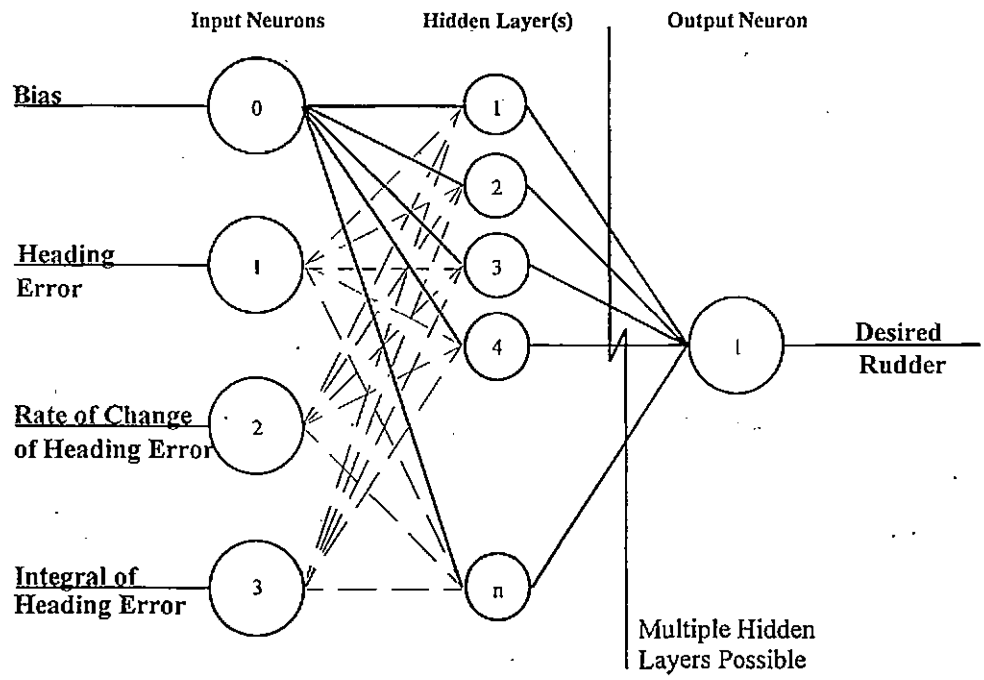

Figure 3.4 Network Architecture

3.5.2 Forward Propagation

The function of an individual artificial neuron was described in section 3.3. By the application of this principle to multiple neurons in a network the strategy of the ANN may be achieved. Each of the four inputs to the ANN is allocated an input neuron, similarly neurons are allocated to the ANN's output(s). Because the back-propagation algorithm is proposed to adjust the weight values (section 3.5.3), the transfer function utilised must be differentiable and therefore the sigmoid function (equation 3.3) was chosen.

$$x_j^s = \frac{1}{1+e^{-I_j^s}} \tag{3.3}$$

In practice, most comparative studies have also used the sigmoid function, the main alternative being the tanh function which complicates the mathematics without offering any additional performance advantage.

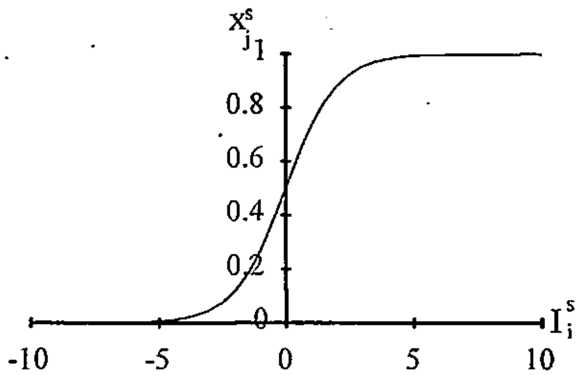

Figure 3.5 The Sigmoid Function

For each neuron in the input layer, the input to the sigmoid function is found by employing equation 3.2. The output of the sigmoid function is then considered to be the output from that neuron The outputs of each of these neurons are then classified as the inputs to the neurons in the next layer. This process continues until in the output layer the sigmoid function will deliver a value in the range 0 to 1, where 0 represents an output of $-\infty$ and 1 an output of $+\infty$. Since these extreme outputs are unrealistic, in reality only outputs in the range 0.1 to 0.9 are worthy of being considered. Scaling must therefore occur so that the desired application output range is obtained within these pre-set limits (equation 3.4).

$$\delta_d = \frac{\delta_{\max} \cdot (y^s_j - 0.5)}{0.4} \tag{3.4}$$

where:

s = output layer.

$j = 1$ (first and only neuron in the output layer).

$\delta_{\max}$ = maximum rudder limits of vessel.

Rudder limits are obviously vessel dependant, typically in the range $\pm 20^\circ$ to $\pm 30^\circ$.

3.5.3 Back-Propagation

The Back-Propagation Algorithm (BPA) is a means of obtaining an optimal set of weight values for a given network, and is the most common form of training currently employed in supervised learning ANNs. The learning is achieved by the continuous presentation of sets of training data which represent the desired system output(s) for given input states. Whilst this technique ensures that no detailed knowledge of the system is required by the controller, it is also reliant upon the quality and quantity of the training data. Even when fully trained, the controller produced will be restricted in performance to the operating envelope to which it was subjected during the learning phase.

Taking each set of training data in turn, the input values are applied to the network using the forward propagation technique and a network output obtained. This output, called the actual output (a), is then compared to the desired output (d) contained in the training data to obtain a global error (E), i.e. an error in system output (equation 3.5). For this comparison to be worthwhile scaling of the training data is required to ensure that the desired output is in the range 0.1 to 0.9 corresponding to the range of the network output.

$$E_j^s = 0.5 \cdot (d_j^s - a_j^s)^2 \tag{3.5}$$

where:

$s = 3$ for the output layer.

$j = 1$ for the sole output neuron.

Multiplication by 0.5 is included to cancel the effects caused by the square term during differentiation. Alternative functions may also be utilised although equation 3.5 is the most common, and therefore considered to be the standard, formation of the global error term.

It is important to remember that the aim of the BPA is to minimise this global error. Therefore, for the given input conditions, the output neuron's weights need to be manipulated in such a manner that the change in value of the weights will ensure a more effective performance level in subsequent activations (equation 3.6).

$$\Delta w_{ji}^{s} = -\eta \frac{\partial E_{j}^{s}}{\partial w_{ji}^{s}} \tag{3.6}$$

where:

η = Learning Rate.

i = neuron in preceding layer from which input has been derived.

The output neuron has a weight on each input connection numbered from 0 to n. Equation 3.6 is therefore true in the case of each weight in turn. However, the global error utilised to determine the weight change is a function of the actual output (a_{1}^{3}), which in turn is a function of the total summed inputs to that neuron (I_{1}^{3}). For the general case of the input weights of the output neuron, the right-hand side of equation 3.6 may be re-written (equation 3.7):

$$\frac{\partial E_{j}^{s}}{\partial w_{ji}^{s}} = \frac{\partial E_{j}^{s}}{\partial I_{j}^{s}} \cdot \frac{\partial I_{j}^{s}}{\partial w_{ji}^{s}} \tag{3.7}$$

Given that:

$$\frac{\partial I_{j}^{s}}{\partial w_{ji}^{s}} = \frac{\partial \sum_{i=0}^{n} x_{i}^{s-1} w_{ji}^{s}}{\partial w_{ji}^{s}}$$

1

$$\frac{\partial I_{j}^{s}}{\partial w_{ji}^{s}} = x_{i}^{s-1} \tag{3.8}$$

and defining :

$$\delta_j^s = -\frac{\partial E_j^s}{\partial I_j^s} \tag{3.9}$$

it is now possible to simplify equation 3.6 using the results obtained from equations 3.8 and 3.9:

$$\Delta w_{ji}^s = \eta \cdot \delta_j^s \cdot x_i^{s-1} \tag{3.10}$$

Analysis of equation 3.10 shows that whilst δ_j^s is defined in equation 3.9 as being the partial derivative of the global error with respect to the total input for the output neuron, the global error is in fact a function of the actual output, and the actual output a function of the total input. Therefore:

$$\frac{\partial E_j^s}{\partial I_j^s} = \frac{\partial E_j^s}{\partial a_j^s} \cdot \frac{\partial a_j^s}{\partial I_j^s} \tag{3.11}$$

where equation 3.12 is the derivative of equation 3.5 and may be defined as:

$$\frac{\partial E_j^s}{\partial a_j^s} = -(d_j^s - a_j^s) \tag{3.12}$$

In a similar fashion the relationship between the total input and the output is based on the transfer function which in this application is the sigmoid function as was defined in equation 3.3. Therefore:

$$\frac{\partial a_j^s}{\partial I_j^s} = \frac{\partial \left[\frac{1}{1+e^{-I_j^s}} \right]}{\partial I_j^s} \tag{3.13}$$

$$\frac{\partial a_j^s}{\partial I_j^s} = -\frac{1}{(1+e^{-I_j^s})^2} \cdot (-e^{-I_j^s})$$

$$\frac{\partial a_j^s}{\partial I_j^s} = \frac{e^{-I_j^s}}{(1+e^{-I_j^s})^2}$$

$$\frac{\partial a_j^s}{\partial I_j^s} = \frac{1}{1+e^{-I_j^s}} - \left[\frac{1}{1+e^{I_j^s}}\right]^2$$

Substituting from equation 3.3 gives:

$$\frac{\partial a_j^s}{\partial I_j^s} = a_j^s - (a_j^s)^2$$

$$\frac{\partial a_j^s}{\partial I_j^s} = a_j^s \cdot (1 - a_j^s) \tag{3.14}$$

Therefore equation 3.9 becomes:

$$\delta_j^s = a_j^s \cdot (1 - a_j^s) \cdot (d_j^s - a_j^s) \tag{3.15}$$

and equation 3.10 may now be detailed as being:

$$\Delta w_{ji}^s = \eta \cdot (d_j^s - a_j^s) \cdot a_j^s \cdot (1 - a_j^s) \cdot x_i^{s-1} \tag{3.16}$$

By implementing equation 3.16 for each of the weights associated with the output neuron, a change in the desired value of that weight may be determined based on the global error of the network. A similar principle must therefore be applied to any hidden layers in the network. However, for these layers an error between actual and desired outputs cannot be used since the required output from any particular neuron is unknown. It must therefore be considered that the error formed at a local level within the network at each neuron output is a function of the global error of the entire network. This assumption must be true since it is through a combination of the local outputs that the global output, and hence the global error, is produced.

In the layer previous to the output layer, equation 3.12 is not valid and must be derived from the error found in the output layer itself:

$$\frac{\partial E_j^s}{\partial a_j^s} = \sum \frac{\partial E_j^s}{\partial I_j^{s+1}} \cdot \frac{\partial I_j^{s+1}}{\partial a_j^s} \tag{3.17}$$

However, by substituting equation 3.1 and 3.9 into 3.17, the resultant expression is:

$$\frac{\partial E_j^s}{\partial a_j^s} = \sum \delta_j^{s+1} \cdot w_{ji}^{s+1}$$

For internal layers of the network, the weight change is therefore dependant upon the δ value of the subsequent layer, giving a generalised internal equation (3.18), corresponding to the earlier output equation 3.15:

$$\delta_j^s = x_j^s \cdot (1 - x_j^s) \cdot \sum \delta_{ji}^{s+1} w_{ji}^{s+1} \tag{3.18}$$

Given the manner in which the BPA operates, it is necessary to have initial weight values in the network so that the first forward propagation may take place to obtain the global error. Considering equation 3.18 it can be seen that if these weight values were identical then any subsequent weight changes would also be the same due to equal values of δ. To achieve a network possible of performing in an optimum fashion, the initial weight values must therefore be in a random form.

The BPA mechanism for weight changes is currently widely popular in a range of applications. The connection to pattern recognition becomes immediately apparent when the means of learning is studied. All the data supplied for training purposes is formulated on a pattern approach, i.e., if the inputs were certain values then the outputs should have corresponding values. Given the range of possible operating scenarios to which the controller may be subjected, it is important that during the learning phase the network learns not only the data currently being presented, but also is capable of maintaining a memory feature of past experiences so that previous learning is not lost. To achieve this aim, four adaptations to the basic BPA can be included, these are:

- Learning Rate.
- Momentum.
- Epoch Size.
- Random Data Presentation.

The Learning Rate, as was declared in equation 3.6, is a multiplicative term to restrict, or enhance, the speed of learning of the network. Whilst it would appear most desirable to maintain the highest speed of learning possible, in practice, performance of the final network is in fact greater with the introduction of a learning rate. Learning based on an individual set of training data provides an extremely narrow view of the overall network performance within its operating envelope. The learning rate therefore restricts the momentary learning so that a reduced emphasis is applied to the current state.

Using the gradient of descent approach, the BPA can find a local minimum in its learning, rather than locating the global minima (Figure 3.6). The momentum term therefore gives the learning mechanism the ability to pass through local minima and on to the global minimum. However, it also restricts the chances of being able to cease learning when that global value has been obtained. Often an overshoot and a corrective back-track is required. It is therefore necessary to control the magnitude of the momentum term which is process-dependant to enable optimum learning to be possible.

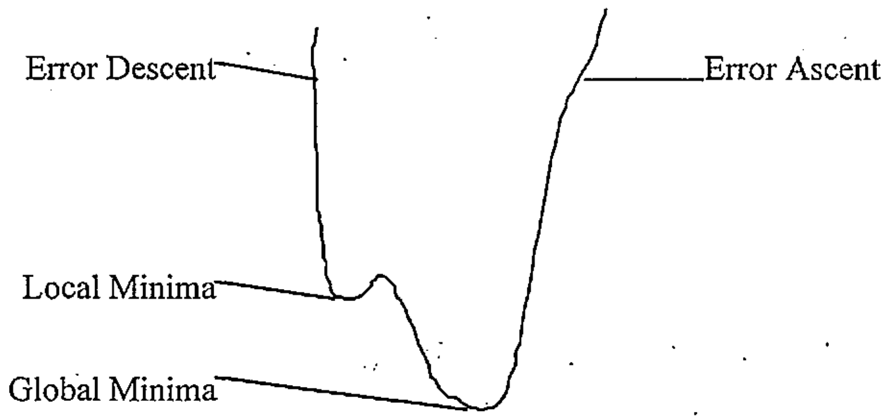

Figure 3.6 Learning Difficulties With BPA

The momentum effect is achieved by the incorporation into the current weight modification of an element of the previous change (equation 3.19). This historical inclusion is capable of eliminating local effects whilst maintaining the overall direction of learning.

$$\Delta w_{ji}^{s}(t) = \eta \cdot \delta \cdot x_{j}^{s-1} + \alpha \cdot \Delta w_{ji}^{s}(t-1) \qquad (3.19)$$

When considering data for training, it is often advantageous to utilise not the global error from one set of training data, but an averaged value generated by a set of data. The amount of data in the set is called the epoch size and is varied depending upon the range and quantity of the data found in the training file. Should the performance envelope be wide, then this approach enables the network to learn a more general understanding of the intended operation instead of specific response patterns.

If the data utilised for training purposes is presented in its original form, then it is highly likely that data representing specific operating conditions will occur in batches. The network will therefore be learning one set of conditions and then replace this knowledge with another set. In the final stages of learning the only remaining capabilities will be for the final set of presented data. This feature is undesirable and may be overcome by the presentation of random data patterns from throughout the training data file. This method ensures that the network is being continuously stimulated and therefore learning right across the operating envelope.

3.6 REQUIREMENTS FOR INTELLIGENT OPERATION

There are currently a range of adaptive mechanisms being proffered as extensions to the ANN principles presented in this thesis. If forward development is to be obtained for the ANN then there is a requirement for the replacement of the BPA supervised learning mechanism, with either the option of Learning with a Critic or Unsupervised Learning.

In the case of Learning with a Critic, there is a requirement for a form of performance assessment to evaluate the success, or otherwise, of the current ANN structure. Only by utilising such a measurement can weight modifications be identified as being correct. The simplest form of this style of learning may be considered to be the addition of a cost function to the basic BPA mechanism. For on-line learning the BPA fails due to a lack of data in the region of the desired network output. It is possible to say, however that the performance of the network is reflected in this application by the performance of the control actuator (the rudder), which in turn is shown by the performance of the actual vessel. Therefore by relating the ship heading error characteristics to a cost function, an estimation of the global error indicative to the network can be produced. Clearly an element of time delay must be imposed on this routine to allow for ship and rudder dynamics. The BPA can therefore be run in an on-line fashion, but the mathematical calculations required for anything other than a small sized network are likely to negate the effectiveness of this type of routine for the small vessel autopilot application.

A quicker and far more satisfactory form of learning is generated by the enhanced Chemotaxis algorithm. Utilising random initial weights values, the forward propagation routine is represented with a full set of input data and a global cost function value obtained. The weight values are then subjected to Gaussian perturbations, the size of which is relative to the magnitude of the cost function derived. If the weight changes proposed enhance the network response, then they are retained, else they are rejected and an alternative set of values calculated. The success of this form of learning is apparent when considering the application advantages. The size of the weight changes will be great only when the network output is largely in error, leaving fine tuning when near an optimal operating point. Since only weight changes which improve performance levels are deemed acceptable, there is a guaranteed corrective learning ability. The use of guided random search methods for weight changes is also considered a faster process than the BPA's gradient of descent, therefore reducing computational time.

Unsupervised principles, e.g. familiarity, clustering, or feature mapping [3.17], may demonstrate the required learning abilities, however the duration of the learning process and the time variant nature of the small vessel, make their implementation impractical for this application.

3.7 DISCUSSION OF ANNS FOR AUTOPILOT DESIGN

This Chapter has presented the basic ANN elements which should be considered if the neural technique is to utilised for the new autopilot design. The forward propagation routine is simple and therefore it should be easy to generate a compact program in "C" to undertake this function. In contrast, the number of weights required to successfully facilitate a control problem of this complexity will be large, probably in excess of 150. The logistics of data storage for this number of weights therefore must be considered.

The required data could be obtained from either sea trials or PC based simulations. It could therefore be possible to train a network to emulate an optimally tuned PID controller in a variety of conditions by teaching the ANN with the data from across the performance envelope. Similarly, the ANN has the potential for future expansion to allow for factors such as velocity, mass loading, wind speed, wind direction and even vessel type. Whilst these inputs are not currently available, there is no reason why this larger and more powerful network could not cope with the added computations, thus providing a vast reservoir of knowledge once training was complete. The scale of the data storage would also have to be increased to match both the increase in input neurons, and the probable need for larger hidden layers within the network.

The possibilities for extension to an intelligent form have been discussed. Whilst this advancement of the ANN is likely to be achievable, the on-line adaption of a large number of weight values will be computationally expensive in terms of both time and code requirements, and is therefore a prohibitive factor when considering the future potential of the ANN autopilot design.

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CHAPTER 4. THE FUZZY LOGIC SOLUTION: PRINCIPLES AND IMPLICATIONS

4.1 INTRODUCTION

Fixed Rulebase Fuzzy Logic (FRFL) has been developed as a means of coping with the decision process when only imprecise data is available to work with. If rigid mathematical relationships between component parts of the process can be defined, then analysis, and subsequent decision making, may be undertaken with relative certainty of a successful conclusion. However, in the cases when such prior understanding is not possible, yet a realistic assessment of the decision outcome is required, the task is considerably more difficult to describe in quantitative terms.

A technique is therefore required which is capable of utilising qualitative, linguistic or just generally imprecise, information. The FRFL technique demonstrates this ability and is consequently generating considerable interest, particularly in the field of control engineering. The concept of FRFL is derived from the principles of Fuzzy Set Theory (FST). Therefore, before a complete understanding of FRFL is possible, it is a pre-requisite that the basics of FST should be described.

4.2 FUZZY SET THEORY

Fuzzy Set Theory, as proposed by Zadeh [4.1], follows the principles of Conventional Set Theory (CST), with one major exception. In CST elements are divided into two categories [4.2], i.e.:

1. Those that belong to a set.
2. Those that do not belong to a set.

The conventional set, (also called the non-fuzzy or crisp set), therefore maintains a distinct difference between elements which are members, and those which are not members of that particular set [4.3]. For example, considering the conventional set describing the vessel length (l) of "about 5 m" (Figure 4.1), the membership function ($\mu(l)$) can be defined as:

$\mu(l) = 0$ (is not a member of the set).

$\mu(l) = 1$ (is a member of the set).

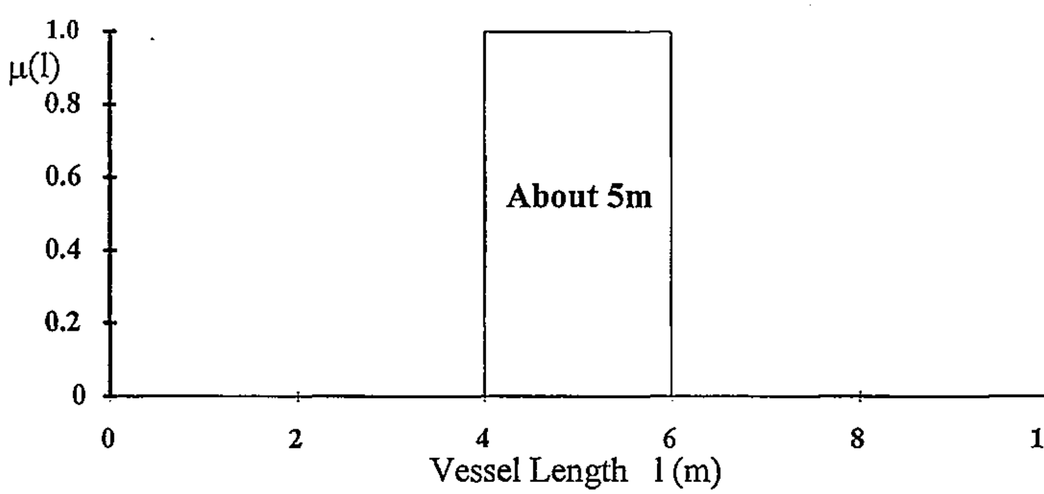

Figure 4.1 Crisp Set for Vessel Length "about 5 m"

In contrast, in FST the elements within the universe of discourse U, over which the set is declared to operate, are assigned a grade of membership between 0 and 1 which describes their degree of membership (Figure 4.2).

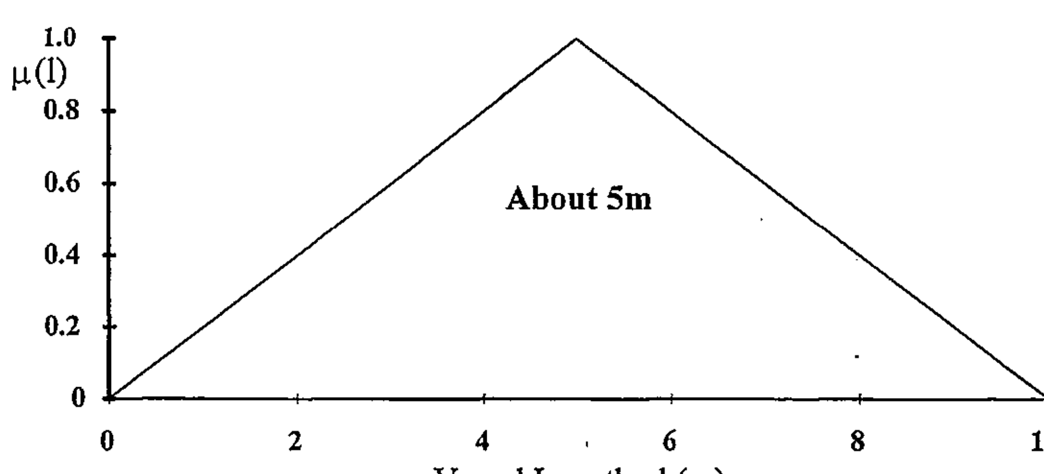

Figure 4.2 Fuzzy Set for Vessel Length "about 5 m"

Within the fuzzy definition utilised for Figure 4.2, the term vessel length may be referred to as the linguistic variable. The fuzzy set "about 5 m" is seen to operate over the entire range 0 to 10 m with the membership value being reduced progressively from 1 to 0 as the distance from the set point (5m) is increased. It is therefore true to state that the point 3 m, where 3 m $\in$ U[0 m.10 m] is a member of the set "about 5 m" with a membership value of :

$$\mu_{10m}(u) = 0.6 \tag{4.1}$$

With CST this point would have been defined by a membership value of 0. It is apparent therefore, how the fuzzy technique allows recognition of the significance of lesser points within the universe of discourse which although not falling within the conventional definition of the set, do in reality portray many of the desirable aspects of that set. The relative degree of similarity with the desired set is encapsulated within the derived membership value.

Mathematically, the discrete fuzzy set (D) may be defined as:

$$D = \sum_{i=1}^{n} \mu_D(u_i) / u_i \tag{4.2}$$

where:

$u_i \in U$

$\mu_D(u_i)$ = membership value of set D at u_i.

For the fuzzy set "about 5 m", with an interval of 1 m and universe of discourse U[0 m.10 m], the discrete description may also be defined as:

$$\text{"about 5 m"} = 0/0 + 0.2/1 + 0.4/2 + 0.6/3 + 0.8/4 + 1.0/5 + 0.8/6 + 0.6/7 + 0.4/8 + 0.2/9 + 0/10 \tag{4.3}$$

4.2.1 MANIPULATIVE OPERATIONS ON FUZZY SETS

Having defined the difference between fuzzy and conventional sets, it is necessary to describe the three basic manipulative operations which are fundamental to most applications, these are:

1. Union of fuzzy sets.
2. Intersection of fuzzy sets.
3. Fuzzy Relationships.

The union operation, when applied to two fuzzy sets P and Q, both of the same universe of discourse (A), is equivalent to a connective OR and is described mathematically as:

$$\mu_{P+Q}(a) = \max[\mu_P(a), \mu_Q(a)] \tag{4.4}$$

where the operation of union is indicated by use of the "+" sign which is equivalent to the conventional $\cup$ sign.

Considering the fuzzy sets describing vessel length, sets named linguistically as short and medium (Figure 4.3) could be defined as:

$$\begin{aligned}\text{short} = {} & 1.0/0 + 0.8/1 + 0.6/2 + 0.4/3 + 0.2/4 + 0/5 + 0/6 + 0/7 \\ & + 0/8 + 0/9 + 0/10\end{aligned}$$

$$\begin{aligned}\text{medium} = {} & 0/0 + 0.2/1 + 0.4/2 + 0.6/3 + 0.8/4 + 1.0/5 + 0.8/6 \\ & + 0.6/7 + 0.4/8 + 0.2/9 + 0/10\end{aligned}$$

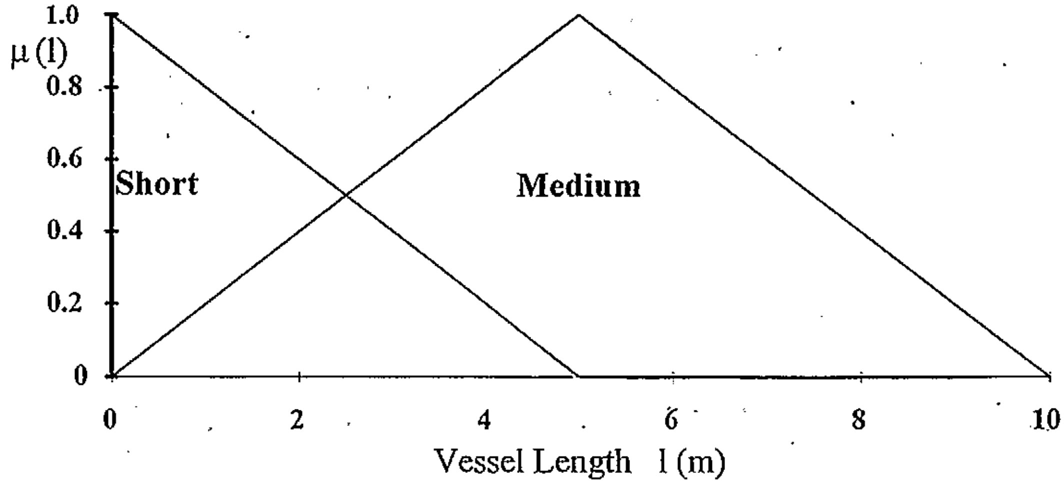

Figure 4.3 Fuzzy Sets Short and Medium

Therefore, by applying this principle of union to the sets short and medium creates a short OR medium set (Figure 4.4).

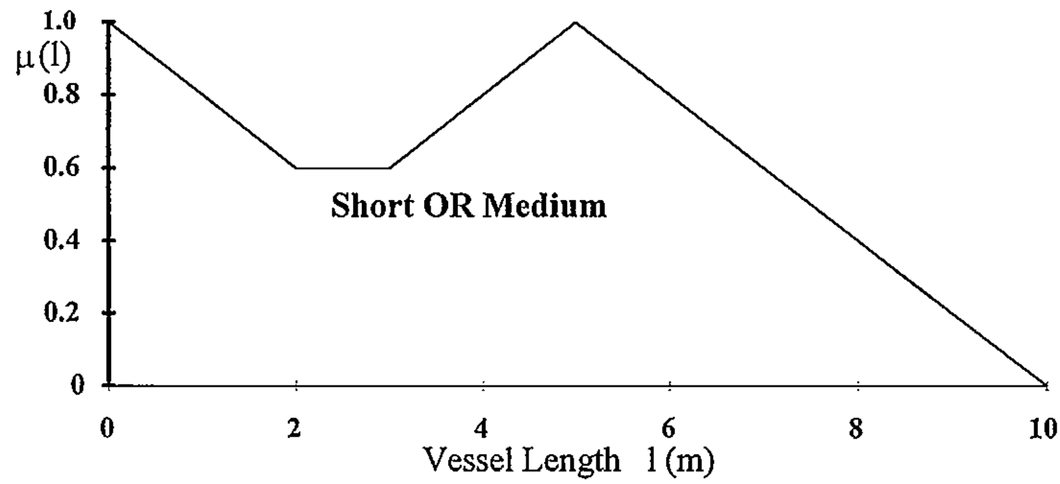

Figure 4.4 Union of Fuzzy Sets Short and Medium

$$\text{short OR medium} = 1.0/0 + 0.8/1 + 0.6/2 + 0.6/3 + 0.8/4 + 1.0/5 + 0.8/6 + 0.6/7 + 0.4/8 + 0.2/9 + 0/10$$

In a similar manner, the operation of intersection when applied to two fuzzy sets P and Q, of the same universe of discourse (A), is equivalent to a connective AND, and may be defined mathematically as:

$$\mu_{P \cap Q}(a) = \min[\mu_P(a), \mu_Q(a)] \tag{4.5}$$

where the operation of intersection is indicted by the $\cap$ sign. By the application of the operation of intersection to the fuzzy sets short and medium describing vessel length creates a new short AND medium set (Figure 4.5).

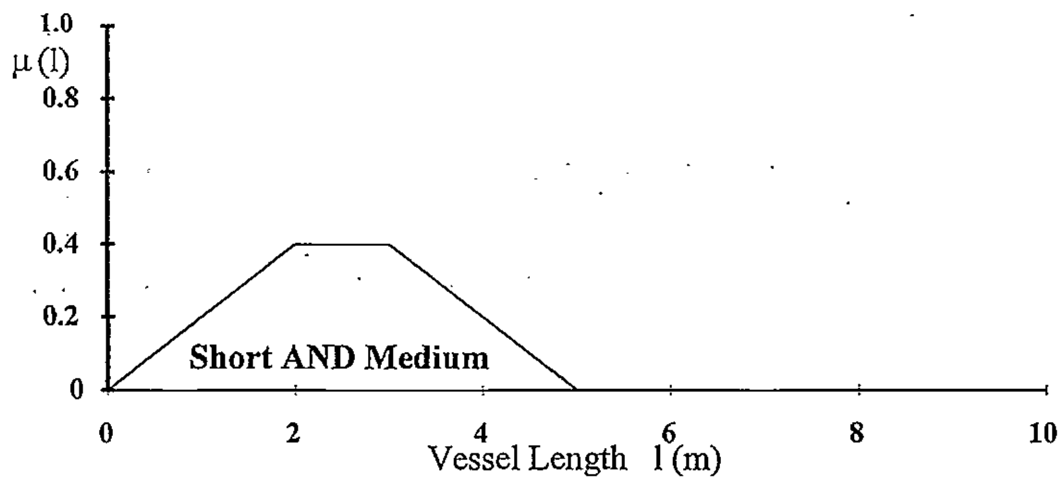

Figure 4.5 Intersection of Fuzzy Sets Short and Medium

$$\text{Short AND Medium} = 0/1 + 0.2/1 + 0.4/2 + 0.4/3 + 0.2/4 + 0/5 + 0/6 + 0/7 + 0/8 + 0/9 + 0/10$$

The fuzzy relationship is based on linguistic implication between an antecedent (P) and its corresponding consequent (Q), where P and Q are two fuzzy sets and are of different universes of discourse (A) and (B), e.g.

IF P THEN Q

or,

$$R = P \times Q \tag{4.6}$$

where R represents the relationship and the $\times$ sign denotes the operation of fuzzy relations. Mathematically, equation 4.6 may be defined as:

$$\begin{aligned} \mu_R(a,b) &= \mu_{P\times Q}(a,b) \\ &= \min[\mu_P(a), \mu_Q(b)] \end{aligned} \tag{4.7}$$

where $a \in A$ and $b \in B$.

Similarly, several fuzzy sets (P, Q, Z) from disparate universes of discourse (A, B, C) may be combined to give a fuzzy conditional statement of the form:

IF P AND Q AND Z THEN R

which mathematically may be written as:

$$R = P \times Q \times Z$$

$$= \min[\mu_P(a), \mu_Q(b), \mu_Z(c)] \tag{4.8}$$

where $a \in A$, $b \in B$ and $c \in C$.

As an extension of the fuzzy principles, the complement (NOT) of a fuzzy set may be defined, similarly a linguistic hedge, e.g. very, rather, etc. These, and many other, fuzzy manipulative operations are described in detail in the original proposal by Zadeh [4.4]. However, a more recent and applicable review of the technique may be found in the work of Sutton and Towill [4.5], where a tutorial explanation of the use of fuzzy sets is presented.

4.3 THE EARLY DEVELOPMENT OF FUZZY LOGIC

Following the proposition of FST by Zadeh [4.4] in 1965 and later developments [4.6], the potential for control situations was realised. The initial published control application was by Mamdani and Assilian [4.7] in 1975, when fuzzy techniques were applied to the control of engine speed and boiler pressure for a small steam engine. Although a non-linear problem, the fuzzy method was found to outperform the conventional tuned controller. The particular advantage was the ability of the new controller to be relatively insensitive to alterations in its operating environment.

In the subsequent year results were published by Kickert and van Nauta Lemke [4.8] concerning their application of fuzzy logic to a warm water plant. When attempting to control the exiting water temperature, whilst maintaining a fast response time to temperature step changes, the fuzzy controller demonstrated a far superior transient and steady state response than the original optimised Proportional plus Integral (PI) controller.

Following this period, a series of important applications were proposed [4.9 to 4.13] that indicated the enormous potential of fuzzy logic in control situations that are either non-linear and/or time varying. Since that time the emphasis has broadened to encompass a much wider spectrum of applications including many which have entered into the consumer's market place, e.g. rice cookers, cameras etc. An excellent review of fuzzy logic and its early development may be found in the work by Tong [4.14] and should certainly be considered as further reading.

4.4 CONSIDERATION OF A FUZZY LOGIC AUTOPILOT

Classical and modern control theories have been utilised for many years to overcome successfully control problems where the system is linear in nature and may be described mathematically. Many systems, e.g. ship dynamics, are non-linear and/or time-variant systems. Therefore, these conventional approaches are not always capable of designing a controller that can fully match the system's requirements.

In many such cases the system was operated, prior to automation, by a human operator who would undertake manual adjustments in order that a successful and acceptable level of control was maintained. It is thought that the ability of the human operator to cope with system non-linearities can be linked to their imprecise operating manner, i.e. inputs to the human operator are often in the form of :

"big" input is registered so therefore a "big" output is required.

Whilst the exact definition of "big" may be non-existent, there is certainly a "feel" that one value may be "big" and another may not. Perhaps then to put a precise value on the term "big" would destroy the imprecision and general vagueness of the human control strategy, thereby reducing our ability to cope with such a range of situations and circumstances.

If control techniques fail where human instinct was successful, then there is a clear reason for pursuing a path towards an automatic controller with a more human like reasoning mechanism. Such a device is thought to be the Fuzzy Logic Controller (FLC) which utilises imprecise fuzzy sets and relationships.

The basic design of a standard form of FLC contains three elements, these are:

1. Fuzzification of inputs using fuzzy windows.
2. Defuzzification of outputs using fuzzy windows.
3. Rulebase relating fuzzy inputs to fuzzy outputs.

4.4.1 INPUT FUZZIFICATION

Fuzzification is the methodology by which the "real world" deterministic inputs may be transformed into a fuzzy format for utilisation with the FLC. Previous autopilot applications [4.15, 4.16] of fuzzy logic have restricted the inputs to those of heading error and rate of change of heading error, each variable being fuzzified individually by employing a fuzzy window which contains a series of fuzzy sets. The chosen fuzzy sets are deemed to represent the working envelope of the controller for a particular input variable. However, the number and position of the sets is design-shape and application dependant. Typical shapes include triangular, trapezoidal and gaussian sets. For the purpose of computational efficiency, the triangular shaped sets require the least amount of storage capacity and are comparatively easy to design since they operate about a clearly distinct set point. The set point can be defined as the point at which the function describing the set has a membership value of unity.

As the number of utilised sets is raised, so the complexities of the FLC increase greatly. It is therefore important that the set number is minimised for any application where computational storage and power is restricted by physical limits. Conversely, if the number of sets for each window is too low, then the range of permutations used to derive the controller outputs becomes restricted and only linear control possible. The traditional approach is to utilise an odd number of fuzzy sets, with the central set being positioned about the zero input condition. The input window's universe of discourse is defined using the minimum number of discrete intervals, at each interval the sets having a membership value in the range zero to unity. Input resolution is directly related to the number of intervals used and must be considered when designing the input windows.

Each set is given a linguistic label to identify it, in the range Positive Big (PB), Positive Medium (PM), Positive Small (PS), About Zero (Z), Negative Small (NS), Negative Medium (NM) and Negative Big (NB). The identical window design can then be utilised for both inputs to conserve required memory storage in accordance with the hardware restrictions for implementation discussed in Appendix A, only the window limits being varied in each case. The values applied to the window limits should be large for course-changing operations when the inputs of heading error and rate of change of heading error are likely to themselves be large, e.g. approximately ±180° and ±3.0°s^{-1}. Conversely for course-keeping operations the required window limits are likely to be small, e.g. approximately ±5.0° and ±1.0°s^{-1}. To meet the required input resolution of 0.1° for heading error in the range ±5.0°, the relevant input window would need to be defined by at least 100 intervals for each fuzzy set given a total of 700 defined points for a typical seven set window. In the case of the course-changing mode, the subsequent data storage problem explodes to create even greater difficulties due to the larger window limits.

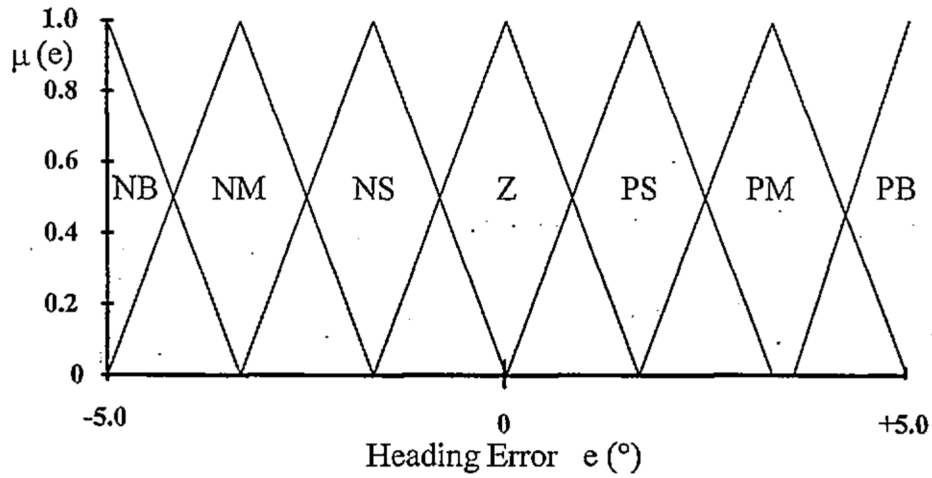

Figure 4.6 Typical Seven Set Fuzzy Input Window for Heading Error

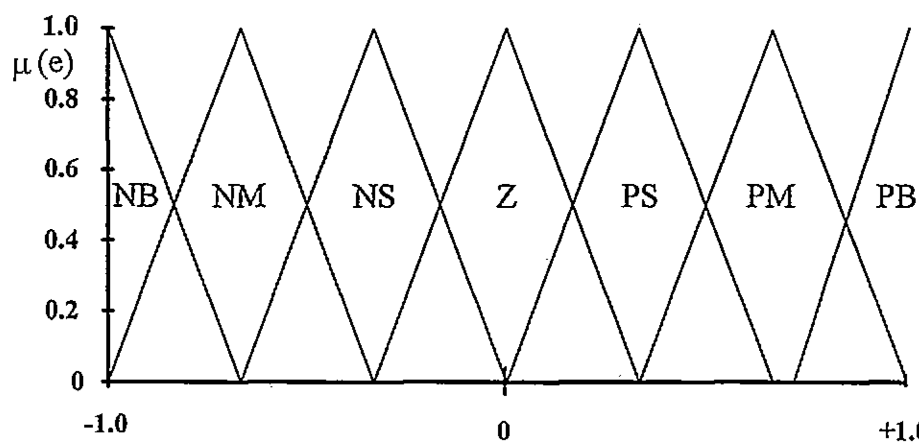

Figure 4.7 Typical Seven Set Fuzzy Input Window for Rate of Change of Heading Error

The set point positions determine the position of each set within the window and should therefore be placed in such a manner that they represent the positions where a change is controller action is required. As the fuzzy sets within the Window overlap, then a transition between differing control strategies may be enforced. The speed of this transition is dictated largely by the degree of overlap between fuzzy sets and the fuzzy significance of the sets in question. In the case of input values which fall outside the extremities of the input windows, these values are normally saturated to the size of the window limits. It is therefore essential that the input windows cover the actual full range of useful inputs, as no new control configurations are possible for inputs which fall within the saturated regions.

Having defined the input window for each of the input variables, the fuzzification mechanism may be initiated. The input variables are applied to their respective windows. If they fall outside of the window limits, then they are saturated to the value of the window limits. The fuzzy sets contained within the input window may be linked together by a union (max) operation. Therefore, for any given input within the window, it becomes possible to evaluate which fuzzy set is "hit" with the maximum membership value. In many cases more than one set may be "hit", and in this instance the membership values should be considered in order of their significance. Whilst it is possible to design a FLC which operates using only the single most maximum membership from each input window, it must be recognised that the imprecise ability of the control strategy is severely impaired since the entire conceptual basis of the FLC is founded in both the applied grade of membership and the union of one or more fuzzy sets to describe an individual occurrence or event. By imposing the limitation of the single maximum membership, the fuzzified version of the real world deterministic value is confined to a single fuzzy set. The necessity for recognition of at least the two largest maximum values is therefore established. However, should three or more such values be utilised, then the number of permutations for internal fuzzy relationships escalates rapidly. Whilst these less significant memberships are greater than zero, their magnitude is normally small. It is therefore ineffectual to include more than two maximum membership values other than to increase FLC complexity.

By applying the given approach of fuzzification to the input window describing the inputs of heading error and rate of change of heading error in turn, it is possible to convert each deterministic input value into two fuzzy membership values with their associated fuzzy sets, where one membership is the maximum value for any set in the window for the point defined by the input, and the other is the next to maximum

value. The two sets associated with these two membership values are therefore the fuzzy sets which best describe the respective input.
The procedure of fuzzification is therefore complete with each input being fully described by the two fuzzy sets in each case with the maximum membership values.

4.4.2 OUTPUT DEFUZZIFICATION

Defuzzification is the process by which a fuzzy output value may be converted into the relevant deterministic value for use by the real world. The basic foundation of the fuzzy output mechanism is an output window of similar form to that utilised for the controller inputs. The size of the window limits is restricted by the saturation limits of the control actuator. In this case the control actuator is the rudder, with physical movement limited to approximately ±30°.

Given that the fuzzy output window contains a series of fuzzy sets, and that the fuzzy output will be described in the form of identified fuzzy sets with their associated membership values, then a means of defuzzification is required. It is possible to consider the output to be at the point with the maximum membership. When more than one peak is present then their positions may be averaged. This "mean of the maxim" method has been compared as analogous to a multi-level relay (4.9), however the full concept of fuzziness as derived by the FLC is minimised by the selection of just maximum set memberships since lower membership elements of the output window become irrelevant. An alternative strategy is to apply the "centre of area method" to the entire output window, considering the higher membership value at the point where two active output sets overlap.

This technique is thought to provide a smoother output (4.15) due to the incorporation of the lesser fuzzy elements within the output window. Given the nature of the "centre of area method" it is important to realise that the centre of a symmetrically shaped set will always be in the middle, irrespective of the membership value of that set. This feature of defuzzification is particularly important when only one output set has been "hit", the resulting demanded rudder movement being disjointed. By employing non-symmetrical output sets this undesirable feature of defuzzification may be overcome. Using a similar approach to the design of the input windows, it was found that the typical number of fuzzy sets required to successfully defuzzify a fuzzy controller output is seven. The number of discrete intervals to fully describe the output window's universe of discourse is dependant upon the desired resolution. The final output window design is therefore shown in Figure 4.8:

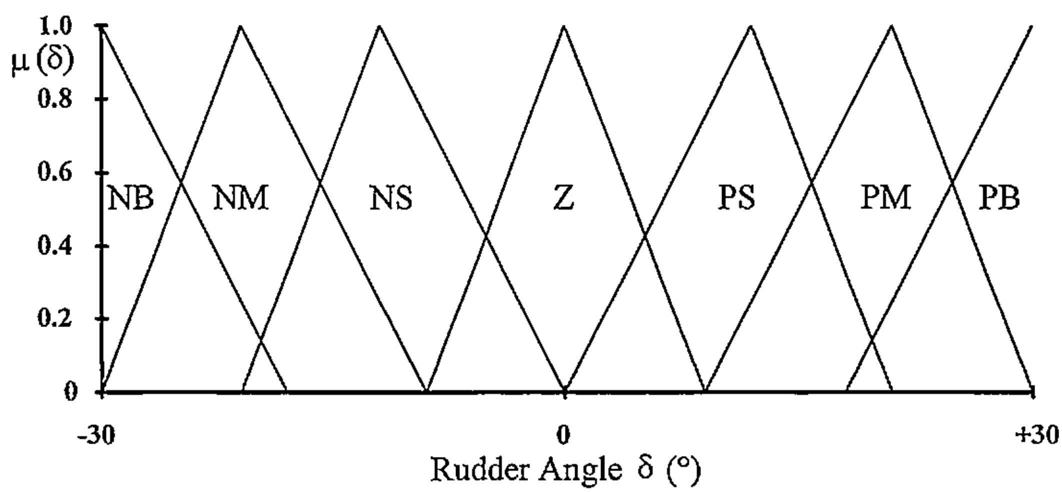

Figure 4.8 Typical Seven Set Fuzzy Output Window for Rudder

Utilising the details of the output window, the "centre of area method" for this application may be defined as:

$$\delta_d = \frac{\sum_{i=-30^\circ}^{+30^\circ} \delta_i \mu(\delta_i)}{\sum_{i=-30^\circ}^{+30^\circ} \mu(\delta_i)} \tag{4.9}$$

where:

δ_d = Deterministic controller output.

δ_i = Discrete interval in universe of discourse δ.

μ = Fuzzy membership at discrete interval δ_i.

4.4.3 FUZZY INTEGRAL ACTION

For this autopilot application an integral action was required to compensate for any constant disturbance effects caused by wind, waves or current. When giving consideration to the incorporation of an integral action, the described form of output window was found to cause difficulties. Whilst it is possible to consider the integral action to be a third input with a corresponding individual input window, the resulting three dimensional rulebase becomes computationally expensive. Separate rulebases may be considered [4.17] which are linked either just before or after defuzzification, however, the additional computer code required for the extra fuzzification/defuzzification prevents this solution from being truly practical.

An alternative method must therefore be derived to enable the successful inclusion of the integral term if fuzzy logic is to be considered for the new autopilot design.

4.4.4 RULEBASE DERIVATION

The fuzzy rulebase is the heart of the FLC and contains the input/output relationships that form the control strategy (Table 4.1).

Rate\Error	NB	NM	NS	Z	PS	PM	PB
NB							
NM							
NS							
Z							
PS							
PM							
PB							

TABLE 4.1 Structure of an Empty Fuzzy Rulebase

Therefore, a large proportion of the FLC's power is contained in this rulebase and determination of the correct magnitudes for each element is essential. The rulebase can be designed using data obtained from the analysis of existing controllers, or by a study of human mariners when controlling small vessels. Using this data in a structured form, a rulebase can be created which specifies which set in the output window should be activated when certain input conditions occur. Rules are only established for the set point positions in the input windows.

4.4.5 INFERENCE TECHNIQUES

No matter how extensive a rulebase becomes, it is unlikely that there will be a rule for every input variation. The declared rules are based on the assumption that the input sets are "hit" with a membership of unity. In practice, it proves very often to be the case, that the exact input set is not available and a nearest set is therefore "hit" instead. When this feature of the FLC occurs, then the membership value of the hit set will be less than unity, therefore the declared fuzzy conditional statement is not wholly true. By use of an inference technique, it is possible to still utilise the given relationship, thus identifying the required output set, however, the membership of the output set is inferred based on the input memberships applied. By employing this technique, the FLC becomes capable of operating in regions not covered by the predetermined input set points. One such inference technique is called the max-min rule of inference (equation 4.11).

$$\mu_{P'}(e) \times \mu_{Q'}(r) \times \mu_Z(\delta) = \max[\min[\mu_{P'}(e), \mu_{Q'}(r), \mu_R(\delta)]] \tag{4.11}$$

where:

$\mu_R(\delta)$ = Defined fuzzy conditional statement between disparate universes of discourse error (e), rate (r), and rudder (δ).

Following this approach, it is possible to deduce the membership of the output set specified by the relationship R given undefined input quantities for heading error and rate of change of heading error. This provides a pessimistic form of control [4.18] which was found to induce low rudder activity in this autopilot application. The relationship between the inputs and the defined relationship is declared by the "min" operation to infer the output set's membership value. The output set "hit" is implied by the definition of the relationship. The union of the rules in the rulebase is then achieved by the overall max function.

An alternative method of inference would be the max-max, or max product, technique. Conversely, this method is thought to give an optimistic performance and in practice was found to produce a more oscillatory rudder movement.

Since the rulebase contains the fuzzy conditional statements between input set permutations, the membership of an identified output set is determined by a minimum operation, as discussed in section 4.2.1.

4.5 REQUIREMENTS FOR INTELLIGENT OPERATION

Compared to the conventional PID autopilot, FLCs are considered to operate in a robust manner when subjected to limited variations in environmental conditions or vessel dynamics in comparison to the conventional PID autopilot. Should large scale dynamic changes be imposed, then the successful operation of the fuzzy logic autopilot becomes questionable. Certainly the required near-optimal performance levels will not be obtainable due to the input to output relationships dictated by the constituent components of the rulebase. In order that autopilot performance may be maintained in such circumstances, the rulebase elements must be adjusted in a fashion that will minimise vessel heading error and rudder activity.

Such a control strategy has been previously been proposed [4.19], and later extended [4.20, 4.21], and is called the Self-Organising Controller (SOC). The basic structure of the SOC may be considered to be a hierarchical system with two levels. The lower level operates in a similar manner to that of the FRFL, whilst the higher level may be considered to be a form of intelligent learning.

The learning mechanism is based upon a performance index (PI) which analyses the current system performance, and derives from this a set of changes to the rulebase to ensure higher performance when subsequently activated. An element of time delay must be imposed on any rulebase modifications to allow for the ship and rudder dynamics. Since both levels of controller operation are continuously active, the rulebase changes may swiftly follow any changes in vessel dynamics or environmental conditions maintaining the autopilot at near optimal performance.

One of the major advantages of this form of intelligent control is due to the predefined PI. Obviously the exact nature of any rulebase alterations is directly related to the content of the PI, but the mathematical content of any such modification is reduced by the pre-implementation design of the PI itself. Similarly the number of elements in the rulebase is restricted by the FLC design, therefore the total amount of rule changes required during one sample period may easily be confined to a relatively low number.

4.6 DISCUSSION OF FUZZY LOGIC FOR AUTOPILOT DESIGN

Within this Chapter the basic elements of a fuzzy logic controller have been presented in relation to the new autopilot design. It would appear that careful consideration must be given to the fuzzification and defuzzification stages if an excessive requirement for data storage is to be avoided. If the window's scope, or number of intervals defining each window, could be significantly reduced, then the potential for using fuzzy logic in this application would be increased enormously.

Due to the nature of the fuzzy mechanism it is apparent that the facility of the rulebase could allow relatively straightforward, but imaginative, pre-design of the controller without the need for extensive files of test data. The ability of the controller to merge a combination of rules, perhaps representing vastly differing control strategies, is without doubt extremely powerful. Similarly, the basic concept of the self-organising controller would appear to offer an on-line learning ability which could be undertaken in the available sample time.

Inclusion the integral action by the described methods would generate an excessive amount of computer code. If the fuzzy logic solution is to be realistic, then an alternative means of incorporation must be devised.

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CHAPTER 5. DETAILED DESIGN OF THE FUZZY LOGIC FOUNDATION AUTOPILOT

5.1 INTRODUCTION

Following the work on neural networks and fuzzy logic described in Chapters 3 and 4 respectively, a decision was required as to which type of controller was to be utilised on the new autopilot. From the discussion in Chapter 3, it is clear that an ANN can easily be modified to cope with a multitude of inputs. However, a considerable quantity of data is required to ensure that the network can learn a correct style of control. Obtaining relevant data is therefore a problem. For the ANN, learning is highly mathematical. Consequently any on-line learning is likely to be very slow and thus unacceptable.

In the case of the fuzzy logic study discussed in Chapter 4, both the basic controller, and the relevant on-line learning principles, appear satisfactory. However, the addition of the third input for integral type action requires further study. Similarly, the need to operate in both course-keeping and course-changing modes without utilising extensive data storage must be overcome for this practical application to be successful.

After consideration of these points, the fuzzy route appears to offer a superior solution for this particular application. Work was therefore carried out on a detailed design of a foundation fuzzy logic autopilot onto which the learning mechanism could be mounted. The potential problem areas in the design were also investigated to obtain a satisfactory resolution.

5.2 NON-LINEAR INPUT WINDOW DESIGN

Following a heuristic design approach, it was found that the minimum number of sets which could successfully describe the inputs for a small vessel autopilot application was seven. However, the use of seven sets requires the central set point to be placed on the zero position in the universe of discourse. In practice the case when inputs are zero is not of significant importance as the control required in this region of the input window may be considered to be linear in nature. Therefore, to employ eight sets with an even distribution of four on either side of the zero position, enables the defined set points to more fully describe the significant controller inputs. The About Zero (Z) set was replaced with two new sets identified by the linguistic labels Positive Tiny (PT) and Negative Tiny NT). Symmetry of these given sets around the zero point enables the zero input condition to be represented by a blend of both positive and negative sets.

In previous maritime studies the two modes of course-keeping and course-changing were treated as either separate modes of operation [5.1], or required the addition of a secondary level rulebase for "close control" [5.2]. Based on the detailed data contained within Chapter 2 of this thesis, combined with personal observations from studying PID autopilot operation, acceptable course-keeping for a small vessel may be classified as being in the range ±1° to ±5°. This specification is dependant upon weather conditions, given that most small vessels would not expect to be at sea in greater than a sea state 5 whilst remaining under autopilot control. It is therefore realistic to consider ±5° to be the necessary limits for the course-keeping input window for heading error. Similarly, for the course-changing mode of operation a large initial rudder is required to bring the vessel about quickly. Detailed consideration of rudder values at this point is not therefore required. Once within approximately 15° of the desired course a more precise level of control is necessary, with the possibility of counter rudder being implemented to prevent the occurrence of any overshoots. The natural window limits for course-changing may therefore be defined as ±15°.

For this application there are insufficient computational resources available to facilitate either separate input windows or rulebases for the two modes of operation.

It is therefore a pre-requisite of this design that both modes be incorporated within the same input window. If eight linear fuzzy sets are employed in this dual purpose input window, then the result for the input of heading error is shown in Figure 5.1.

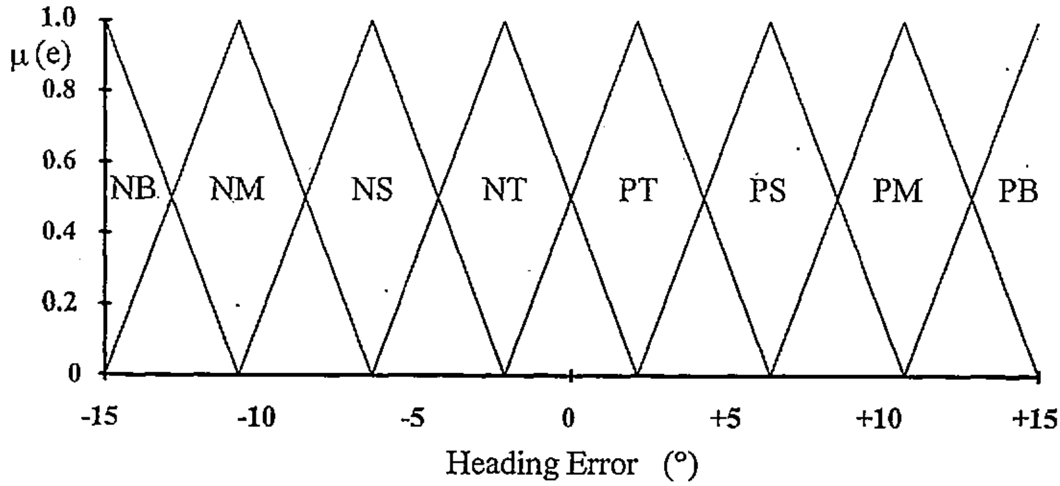

Figure 5.1 Linear Fuzzy Logic Input Window for Heading Error

When considering Figure 5.1 it becomes clear that for the course-keeping mode in the range ±5° there are only two set points. In practice the implication is that all course-keeping situations will be described in the main by these two sets (one positive and the other negative). Only linear control would be possible in this situation. As a design problem, the remaining options to improve on this window's performance would be:

1. Decrease the window limits so that the sets operate closer to the zero point. Although improving course-keeping, this action would ensure that the window limits were too small to allow effect course-changing to take place.

2. Increase the number of sets utilised within the input window. This action would be too computationally expensive.

Whilst in many cases reported in the literature, the fuzzy input sets are symmetrical about their set point, it is possible to design the sets in a non-symmetrical (non-linear) manner. This technique is particularly advantageous when a relatively large universe of discourse is required, as is this case with this application, to provide a high accuracy of control about a point, e.g. zero point, whilst maintaining a minimum number of operational sets. In the small vessel autopilot application, there is a need for a high level of control during course-keeping, i.e. when the course error is within the range ±5°. This effect may be achieved by the utilisation of small angled fuzzy sets, thereby ensuring that several sets operate within the course-keeping performance envelope.

In contrast, during the course-changing mode, the universe of discourse is required to represent a much wider range of heading errors. Therefore, large angled sets are required so that a much larger proportion of the window may be described by each set, thus ensuring that set numbers are to kept to a minimum. At the point when a particular set has a membership value of unity (the set point), it is important to ensure no overlap from adjacent fuzzy sets exists. At the set point the set may therefore be considered to fully describe the input, any activation of the surrounding sets in this situation reduces the importance and thus the effectiveness of any one individual set. By utilising the described non-linear approach, the input window of Figure 5.1 was redesigned with eight non-linear sets. Twenty-one discrete intervals were required to fully describe the new window's universe of discourse (Table 5.1).

Set\$\mu(u_i)$	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
NB	1.0	.75	.50	.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NM	0	.25	.50	.75	1.0	.67	.33	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NS	0	0	0	0	0	.33	.67	1.0	.50	0	0	0	0	0	0	0	0	0	0	0	0
NT	0	0	0	0	0	0	0	0	.50	1.0	.50	0	0	0	0	0	0	0	0	0	0
PT	0	0	0	0	0	0	0	0	0	0	.50	1.0	.50	0	0	0	0	0	0	0	0
PS	0	0	0	0	0	0	0	0	0	0	0	0	.50	1.0	.67	.33	0	0	0	0	0
PM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.33	.67	1.0	.75	.50	.25	0
PB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.25	.50	.75	1.0

Table 5.1 Non-Linear Fuzzy Input Window Definition

The identical window design was utilised for both inputs to conserve required memory storage in accordance with the hardware restrictions for implementation discussed in Appendix A, only the window limits being varied in each case. Using these set definitions, and window limits of ±15° for heading error and ±2°s⁻¹ for rate of change of heading error, the new input window designs are shown in Figures 5.2 and 5.3.

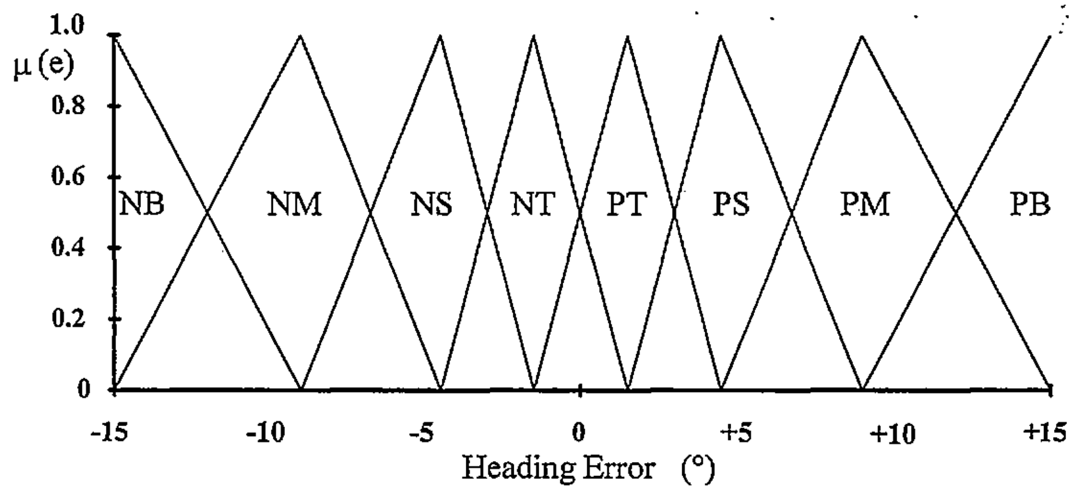

Figure 5.2 Non-Linear Fuzzy Logic Input Window for Heading Error

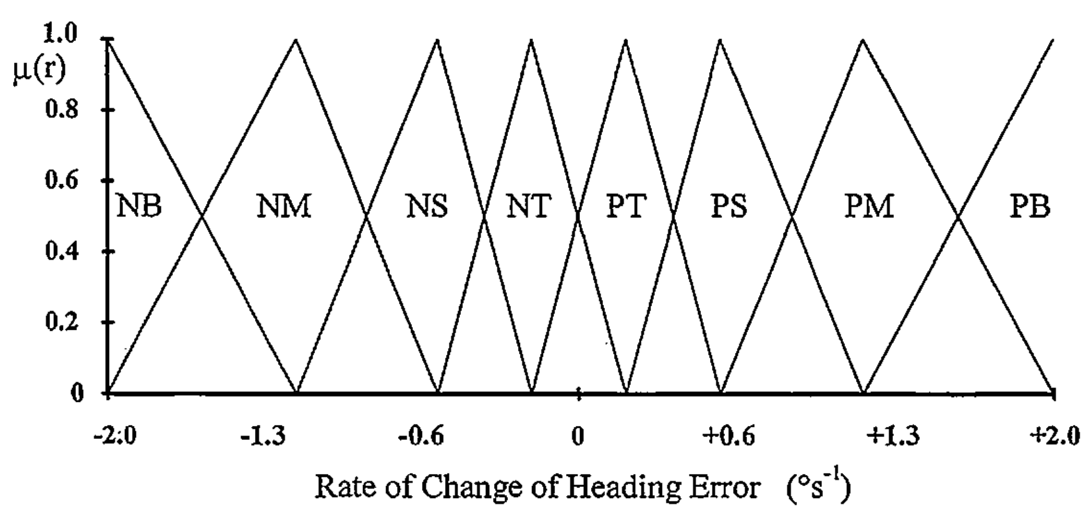

Figure 5.3 Non-Linear Fuzzy Logic Input Window for Rate of Change of Heading Error

The chosen set points for each input window are defined in Table 5.2

Set / Input Variable	Heading Error (°)	Rate of Change of Heading Error (°s^{-1})
NB	-15.0	-2.0
NM	-9.0	-1.2
NS	-4.5	-0.6
NT	-1.5	-0.2
PT	+1.5	+0.2
PS	+4.5	+0.6
PM	+9.0	+1.2
PB	+15.0	+2.0

Table 5.2 Set Points for Fuzzy Input Windows

To reduce the data storage problem, the input windows were defined by twenty-one discrete intervals (0→20) across the entire universe of discourse. Therefore interpolation between defined points was employed to provide a higher fuzzy input resolution to the controller. Using the real world value for heading error with a resolution of 0.1°, fuzzification was undertaken to convert this value in the range covered by the input window definition, i.e. (0 to 20). When fuzzified, a resolution of 0.01 was maintained by equation 5.1.

$$fuzzy\_error = \min(20, \max((real\_error * 0.067) + 10, 0)) \qquad (5.1)$$

where:

$fuzzy\_error$ = heading error after fuzzification

$real\_error$ = heading error before fuzzification

A similar approach was undertaken for rate of change of heading error (equation 5.2):

$$fuzzy\_rate = \min(20, \max((real\_rate * 0.5) + 10, 0)) \tag{5.2}$$

where:

fuzzy_rate = Rate of change of heading error after fuzzification

real_rate = Rate of change of heading error before fuzzification

In both cases, any input values falling outside the working range of the input windows were saturated to the limits of the input windows and thus treated as if they were an input of +15° to -15° or +2°s^{-1} to -2°s^{-1} for each window respectively.

5.3 DEVELOPMENT OF A PSEUDO INTEGRAL ACTION

A new method of employing an integral type action was required which would work within the fuzzy autopilot without utilising the excessive amounts of code size and data storage that was found to occur when integral action was utilised as an excluded third input [5.3]. The magnitude of this problem was mainly due to the additional fuzzification and defuzzification elements necessary within the control routine. These elements were required to define the additional input fuzzification, rulebase, defuzzification associated with the integral term. An excluded input can be defined as an input which operates independently from the main controller input's rulebase and may/may not contribute towards the final output derived from the included inputs. The included inputs are those used determine which rules are activated from the given rulebase, and in this case are heading error and rate of change of heading error.

The integral input could be designed as an included third input to the controller, however the resulting three dimensional rulebase becomes highly expensive computationally.

It is much more computationally efficient to calculate the integral in a novel manner, i.e. in terms of a shift to negative or positive of the established output from the original two input FLC, within the output window limits. This technique is called the Output Set Shift (OSS), equation 5.3:

$$OSS = \min(-100, \max(fuzzy\_average\_error, +100) \tag{5.3}$$

where:

$$fuzzy\_average\_error = \sum_{0}^{n} \frac{\text{TRIM} * fuzzy\_error}{245} \tag{5.4}$$

TRIM = Integral gain with resolution of 0.1

n = number of included samples

In order for this phenomenon to be possible, the conventional output window with only seven fuzzy sets proved ineffective due to the coarse resolution of movement possible. The resolution of this type of integral action is based on the number of set point positions in the output window that the integral output may be assigned to.

A new and somewhat unorthodox style of output window was therefore designed which contained two hundred and one fuzzy singletons, i.e. fuzzy sets with only one element where the membership function has a magnitude greater than zero. Although this may seem excessive, this number of fuzzy singletons was determined to be the minimum number capable of providing a sufficiently high integral resolution, without causing the controller to become either oversized computationally, or disjointed in its demanded control actuator movement. For the operational rudder range of ±30° the possible resolution using the two hundred and one fuzzy singletons is 0.3°. However, using this technique means that the number of output permutations becomes vastly increased and the rulebase must therefore be designed to reflect the full range of output sets, i.e. ±100 sets. To aid this process, the linguistic label for each of the output sets was replaced with a numerical identifier in the range ±100. The new design of output window is therefore of the form given in Figure 5.4.

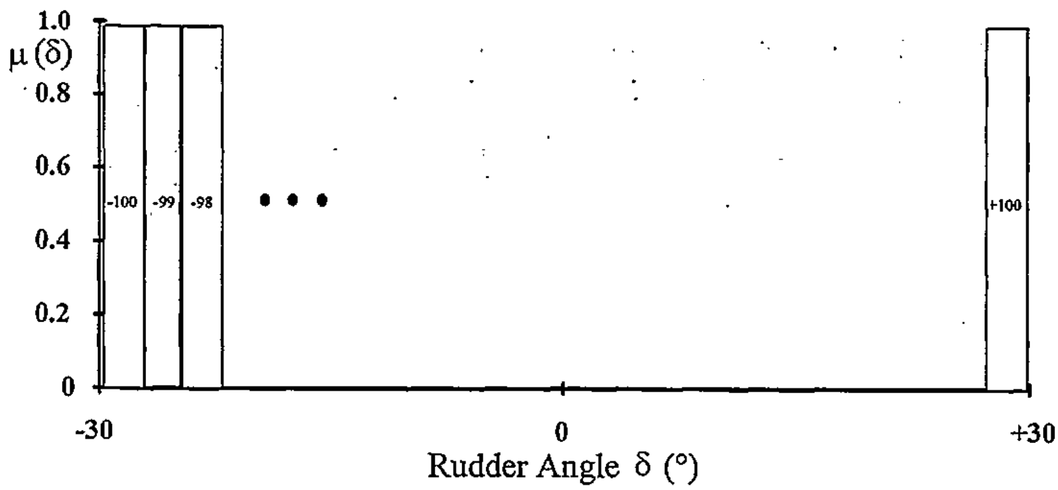

Figure 5.4 Novel Form of Fuzzy Output Window

Similarly, the output defuzzification equation, using the "centre of area method", for this novel form of window becomes:

$$\delta_d = \frac{\sum\limits_{i=-100}^{+100} \delta_i \mu(\delta_i)}{\sum\limits_{i=-100}^{+100} \mu(\delta_i)} \tag{5.5}$$

where:

δ_d = Deterministic controller output.

δ_i = Discrete interval in universe of discourse δ.

μ = Fuzzy membership at discrete interval δ_i.

5.4 FUZZY RULEBASE DESIGN

With any new design, there will be inherent differences from previous versions. Whilst in this case the new design offers the potential for improved autopilot control when compared to the conventional PID autopilot (disregarding any on-line learning ability), it is important that a structured test be carried out to clarify that the new mechanism for control is operating correctly. This operation is best achieved by designing the fuzzy autopilot in such a manner that it emulates the conventional PID version. If a study of the results, following the application of a predetermined set of input data, demonstrates satisfactory similarity, then confidence can be raised that any improved design will also work.

Since it is the fuzzy rulebase which controls what the autopilot is attempting to achieve for any given set of input conditions, it was necessary to design the contents of the rulebase so that for each combination of heading error and rate of change of heading error set points, the rule activated identified an output set that corresponded to the conventional PID autopilot output for the same inputs. The typical gain settings for rudder ratio and counter rudder used with the Cetrek PID controller are given in Table A.4 (section A.2). The conventional fuzzy rulebase was therefore designed to contain output sets which reflected the two hundred and one fuzzy singletons in the output window (Table 5.3).

Rate\Error	NB	NM	NS	NT	PT	PS	PM	PB
NB	-55	-41	-30	-23	-17	-10	+1	+15
NM	-47	-33	-22	-15	-9	-2	+9	+23
NS	-41	-27	-16	-9	-3	+4	+15	+29
NT	-37	-23	-12	-5	+1	+8	+19	+33
PT	-33	-19	-8	-1	+5	+12	+23	+37
PS	-29	-15	-4	+3	+9	+16	+27	+41
PM	-23	-9	+2	+9	-15	+22	+33	+47
PB	-15	-1	+10	+17	+23	+30	+41	+55

TABLE 5.3 Linear Fuzzy Rulebase

To test this autopilot configuration against the PID controller, inputs were applied which described the complete operating envelope covered by the fuzzy input windows for both heading error and rate of change of heading error. Step sizes used were 0.5° for heading error in the range +15° to -15°, and $0.1°s^{-1}$ for rate of change of heading error in the range $+2°s^{-1}$ to $-2°s^{-1}$. The full results from this test are given in Appendix B of this thesis. However, by analysing the results it is clear that generally the fuzzy output was within 0.1° of the PID output. This result is perfectly acceptable, and demonstrates without doubt the validity of the basic fuzzy controller.

Given the non-linear design of the fuzzy input windows, it is possible to further extend the non-linearity of the fuzzy autopilot by modification of the rulebase. By this means the course-keeping action may be retained for small heading errors (sets PT and NT), whilst the set PS and NS may be strengthened to prevent medium/large course deviations from the desired course. This technique should maintain the vessel heading much closer to the desired course than was possible with the PID controller without increasing the PID's gain values. However, when gains were increased, then a tendency to over-react for small heading errors would be produced. Similarly for course-changing, the non-linear rulebase means that high gains with no rate of change of heading error may be employed when heading error is greater than ±15°, and medium/small gains, with a rate of change of heading error, utilised as the heading error reduces to zero. By this means a fast course-changing manoeuvre may be carried out, still with the original accuracy when approaching the desired course. The desired course will therefore be reached in a considerably reduced time. A new non-linear design of rulebase was thus developed (Table 5.4).

Rate\Error	NB	NM	NS	NT	PT	PS	PM	PB
NB	-100	-46	-26	-24	-17	-1	+32	+100
NM	-100	-43	-21	-16	-9	+5	+35	+100
NS	-100	-41	-17	-10	-3	+9	+37	+100
NT	-100	-40	-14	-6	+2	+11	+38	+100
PT	-100	-38	-11	-2	+6	+14	+40	+100
PS	-100	-37	-9	+3	+10	+17	+41	+100
PM	-100	-35	-5	+9	+16	+21	+43	+100
PB	-100	-32	+1	+17	+24	+26	+46	+100

TABLE 5.4 Non-Linear Fuzzy Rulebase

5.5 REVIEW OF NOVEL FUZZY LOGIC AUTOPILOT DESIGN

A novel version of a fuzzy logic autopilot has been designed which operates using two included inputs (heading error and rate of change of heading error) which are fuzzified and applied to a rulebase. The third input (integral) is an excluded input and shifts the rulebase output to positive or negative within the output window,(Figure 6.5). For the integral to have sufficient resolution, the output window was redesigned to contain 201 hundred and one fuzzy singletons. A modified centre of area method was then used to defuzzify the window to obtain a deterministic controller output.

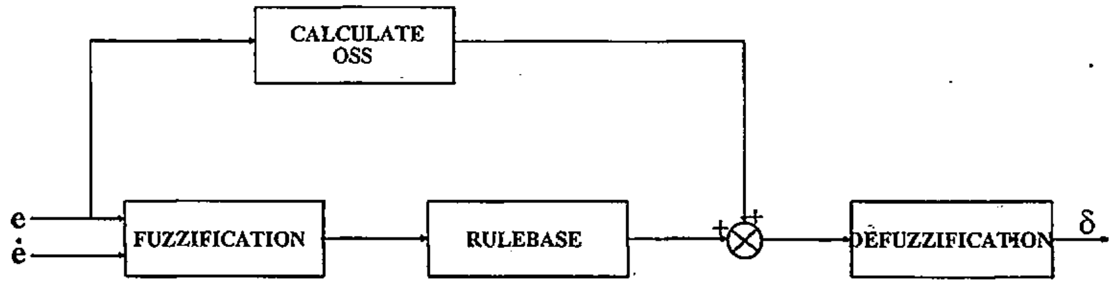

Figure 6.5 Block Diagram of the FLC Layout

The difficulties with the scale of the data storage for the input windows were overcome by using non-linear set shapes. A single window thus combined the requirements for both the course-changing and course-keeping modes of operation without loss of performance. Each window was defined by only twenty-one discrete intervals with interpolation between points to ensure sufficient input resolution was maintained.

By designing the rulebase so that PID emulation was achieved, the operation of the fuzzy controller was validated. The rulebase was then redesigned in a non-linear format which enable delicate control for course-keeping using low gains, and simultaneously fast course-changing using high gains.

The design of the foundation fuzzy logic autopilot may now be considered to be complete. This autopilot design can also be utilised as the basis for the incorporation of a form of intelligent learning, as covered in Chapter 6.

5.6 REFERENCES

5.1 Sutton R. "Fuzzy Sets Models of the Helmsman Steering a Ship in Course-Keeping and Course-Changing Modes." PhD Thesis, RNEC/University of Wales, 1987.

5.2 Farbrother H.N. and Stacey B.A. "Fuzzy Logic Control of a Remotely Operated Submersible." Proc. 1st Int. Conference Manoeuvring and Control of Marine Craft, Exeter, UK, pp 193-210, 1990.

5.3 Polkinghorne M.N., Roberts G.N., and Burns R.S. "Small Marine Vessel Application of a Fuzzy PID Autopilot". Proc. 12th IFAC World Congress, Sydney, Australia, Vol. 5, pp 409-412, 1993.

CHAPTER 6. EXTENSION OF THE FLC DESIGN FOR SELF-ORGANISING OPERATION

6.1 INTRODUCTION

Chapter 5 established the concept of the fuzzy logic foundation autopilot and validated its operation in comparison to the conventional PID controller during the design stage. It must be recognised that this new design of FLC still suffers from the main restriction associated with the PID version, i.e. there is no on-line learning mechanism. The performance ability of the FLC controller, whilst improved across the operating envelope, remains dependant upon the settings for rudder ratio, counter rudder and trim. These values are input into the system by the installation engineer and may be subsequently altered by the mariner. The latter situation is most likely to occur in the majority of situations.

The development of a learning mechanism which can be combined with the established foundation FLC design is therefore essential if the desired overall improvements in performance are to be obtained. Such a mechanism is called the self-organising controller (SOC) which has been derived from an original application by Procyk and Mamdani [6.1] in 1979 and has since evolved to match various applicational requirements. Before describing in detail the manner in which the SOC technique has been applied to this application, it is useful to briefly outline the fundamental SOC principles involved.

6.2 AN UNDERSTANDING OF BASIC SOC PRINCIPLES

The early SOC design has since been applied to a variety control applications [6.2, 6.3 and 6.4]. Additional work by Yamazaki [6.5] and also by Sugiyama [6.6] has advanced the SOC performance capabilities to overcome early problems connected with the speed of learning and the SOC's poor ability to cope with steady-state errors. More recently marine applications have appeared [6.7, 6.8, and 6.9] which utilise the algorithm proposed by Sugiyama. In brief, this algorithm combines the two tasks of control and learning. Control is carried out using traditional fuzzy logic methods as previously described in Chapters 4 and 5. Learning is achieved by observing the operating environment and the controller's effect within that environment. By utilising this information, changes in the fuzzy rulebase are determined in order that future activations of those rules will generate an improved level of performance. Having predetermined which observations are acceptable, and which are not, this information may be stored in a matrix format called a performance index (PI). The content of the PI is indicative of the magnitude of the rule change required. The PI therefore operates in a very similar manner to the fuzzy rulebase described in Chapters 4 and 5. If the observations of the operating environment indicate that the process is maintaining a satisfactory level of performance then no rule alterations will be required. Conversely, as the performance level deteriorates, then the magnitude of the rule changes increases.

For this process to function correctly, it is imperative that the observations are related to the rules that were activated by the control mechanism a period of time previously. This period of time is related to the time constant of the process being controlled and is referred to as the delay in reward. For the majority of the work using the Sugiyama algorithm, an empty rulebase is utilised at the beginning of the process, i.e. no model of the process to be controlled was required by the controller. The content of the rulebase was then built up by the learning mechanism over a period of time until rule convergence is achieved, i.e. no further rule modifications are required as the PI considered that the performance level obtained was that desired.

The key feature of the Sugiyama algorithm was the introduction of four over-rules. These are rules which improve the speed of learning whilst also ensuring that the learning is correct. The rules are process dependant but have been translated into marine terminology by the work of Sutton and Jess [6.9]. The over-rules may therefore be amended for this application and described as:

1. If Heading Error is **Zero**
   & Rate of Change of Heading Error is **Zero**
   Then Rule is **Zero**

2. If Heading Error is **Positive**
   & Rate of Change of Heading Error is **Positive**
   Then Rule is **Positive**

3. If Heading Error is **Negative**
   & Rate of Change of Heading Error is **Negative**
   Then Rule is Negative

4. Rules are **Symmetrical** about the **Zero Position**

To improve the speed of convergence for the rule modification, Sugiyama proposed the introduction of a third input which for this application would be named the rate of rate of change of heading error. The added controller complications of this additional term were counter balanced by the performance advantage obtained. Similarly, to improve controller speed Sugiyama developed a form of non-linear quantisation. Quantisation is a pre-fuzzification step which maps the normalised real world values into a range suitable for use within the SOC, e.g. 0 to 7 for an eight set input window. Weight values were then utilised to combine the closest two sets, thus creating pseudo-continuous inputs, so that resolution was not lost.

6.3 DEVELOPMENT OF A NEW SOC METHODOLOGY

The fundamental concepts of the Sugiyama SOC are therefore the use of the performance index and the supervisory role of the over-rules. Both of these aspects have been proven to operate successfully for a range of applications and can be considered as the basis for this new design of SOC.

To assist with the implementation of the integral action discussed in section 5.3, a two hundred and one fuzzy singleton output window was employed to replace the conventional output window which typically utilised seven fuzzy sets. The fuzzy rulebase was similarly modified to encompass the two hundred and one possible output sets. The design of FLC has significant implications for its potential extension to SOC operation. By increasing the number of output set permutations to two hundred and one , then the number of rule adjustments that can be enforced by the performance index is also increased. In addition, identification of each output set by a numerical label ensures that it is possible to increment, or decrement, the rules mathematically. This facility is not practical when using linguistic labels. Should the performance level of the controller fall and the PI thus dictate that a rule change is required, the two hundred and one possible rule variations which can be chosen provides, for the case when the Max Rud Ang setting is 9 equating to a rudder range of $\pm 30°$, a resolution of a $0.3°$.

The concept of the rulebase being empty, with subsequent learning to generate the correct rules, is not practical for this application. A vessel at sea with no control initially, then poor control during learning, followed by optimal control after convergence would create considerable safety problems. No vessel should be at sea under autopilot control unless that control is both predictable to other vessels, and corrective in nature with respect to the heading error. It could be argued that such learning would be a "one off" operation with the results being subsequently recalled from memory when the autopilot routine was activated. In practice, due to the time-variant nature of both the vessel dynamics and of the environmental conditions, such learning only meets the vessel's requirements at that particular time and will thus represent only a rough guide to the vessel's control requirements at any point in the future. Since a rough estimate of the performance requirements is already available in the form of the pre-set gain values for rudder ratio, counter rudder and trim, it is more realistic to attempt to incorporate this information into an elementary rulebase which could be finely tuned on-line using the SOC learning mechanism. By this means the autopilot always retains the capability to control the vessel. Safety, predictability and minimum performance levels can thus be ensured at all times.

The fuzzy rulebase developed in Chapter 6 utilised typical gain values for rudder ratio and counter rudder of 6 and 3 respectively. However, gain values must be variable to allow the mariner the facility of adjustment. Thus to utilise a rulebase with defined values in this manner restricts the ability to enforce any desired gain alterations. Similarly the proportional and derivative functions must be considered as separate features of the control mechanism since they may need to be modified independently, e.g. a condition may arise when an increase in rudder ratio is required but the counter rudder performance remains acceptable and therefore should not be changed. Given this situation, to modify a rule which represented the output set derived from both gain terms could induce a detrimental effect on the controller's performance. However, the rulebase has the ability to incorporate the desired non-linear effects developed in Chapter 5. This facility must be considered to be critical if the SOC design is to meet the required levels of performance, and should not therefore be removed. After consideration of the rulebase and its associated facilities and requirements, a new SOC component called an enhancement matrix is now proposed which will replace the rulebase whilst retaining the essential operations which it carried out in addition to several improved features.

6.4 ENHANCEMENT MATRIX DESIGN

Instead of the being identified from the rulebase, the four "hit" output sets may be determined by a linear calculation (equation 6.1).

$$fuzzy\_output_{\mathrm{n}} = \min\left(+100, \max\left(\frac{fuzzy\_error * \mathrm{RR}}{\mathrm{x}} + \frac{fuzzy\_rate * \mathrm{CR}}{\mathrm{y}}, -100\right)\right) \tag{6.1}$$

where:

fuzzy_output	= Fuzzified output for use in the fuzzy output window
n	= n^{th} output set in the range 1 to 4
fuzzy_error	= Fuzzified heading error
fuzzy_rate	= Fuzzified rate of change of heading error
RR	= Rudder ratio (proportional gain)
CR	= Counter rudder (derivative gain)
x,y	= conversion factors to the output set range of ±100 (201 fuzzy singletons) with a resolution of 0.05°.

This means of generating the required output set is relatively simplistic and contains no non-linear effects. In addition, much of the ability of the FLC to derive a deterministic output from imprecise input data is lost. However, by employing the use of the enhancement matrix (EM) the desirable features of the FLC, e.g. non-linear effects and capability to cope with imprecision, may be recovered, with additional benefits, e.g. use with variable RR/CR gain settings and separation of rudder ratio and counter rudder effects for precise learning, also occurring.

The EM operates in a similar manner to the fuzzy rulebase and has the same dimensional specification as the rulebase developed previously for the foundation FLC. Similarly, the inputs to the EM remain heading error and rate of change of counter rudder gain terms. The important difference between the EM and the traditional rulebase is that the content of the EM does not identify an output set, instead each EM represents an enhancement to the represented gain term (rudder ratio or counter rudder) which can vary, given the combination of input conditions.

At an initial level the EM is designed to contain the non-linear aspects contained within the FLC rulebase. Because the EM is accessed using the fuzzified input data for heading error and rate of change of heading error, then the fuzzy abilities previously demonstrated in the earlier foundation FLC design may be restored.

However, there are two key reasons why the introduction of the EM is critical for the development of the SOC:

1. The contents of each EM is non-dimensional and is expressed as a percentage change based on the current RR and CR gain settings. It may therefore be considered as valid irrespective of the gain settings for rudder ratio and counter rudder. This feature enables variable gain settings to be introduced by the mariner or by an installation engineer. The resulting FLC is therefore much more flexible, and realistic, when considering the expected operating situation.

2. The two functions invoked by rudder ratio and counter rudder have been separated. When learning is required from the SOC mechanism, it is possible to identify and thus modify the two gain terms independently from each other. The potential learning power of the SOC is therefore greatly increased by this facility. In addition the delicacy with which precise levels of learning may be achieved is also greatly enhanced.

As before, the EMs designed above attempt to replicate the conventional PID control, for the utilised gain values, around the set point. However, as the magnitude of the heading error increases, then so does the aggregate rudder ratio, i.e. the combined rudder ratio value plus the enhancement from the EM. Conversely, for rate of change of heading error, as the magnitude of the heading error increases, then the enhancement from the EM becomes more negative, i.e. the effective aggregate counter rudder value is reduced. These non-linear effects were found to improve the course-keeping and course-changing responses during autopilot operation. As an initial point from which the learning algorithm could commence, two EMs were designed (Tables 6.1 and 6.2) encapsulating the non-linear effects from the original FLC rulebase .

Rate\Error	NB	NM	NS	NT	PT	PS	PM	PB
NB	+200	+100	+33	0	0	+33	+100	+200
NM	+200	+100	+33	0	0	+33	+100	+200
NS	+200	+100	+33	0	0	+33	+100	+200
NT	+200	+100	+33	0	0	+33	+100	+200
PT	+200	+100	+33	0	0	+33	+100	+200
PS	+200	+100	+33	0	0	+33	+100	+200
PM	+200	+100	+33	0	0	+33	+100	+200
PB	+200	+100	+33	0	0	+33	+100	+200

Table 6.1 Enhancement Matrix for Rudder Ratio

Rate\Error	NB	NM	NS	NT	PT	PS	PM	PB
NB	-100	-100	-67	0	0	-67	-100	-100
NM	-100	-100	-67	0	0	-67	-100	-100
NS	-100	-100	-67	0	0	-67	-100	-100
NT	-100	-100	-67	0	0	-67	-100	-100
PT	-100	-100	-67	0	0	-67	-100	-100
PS	-100	-100	-67	0	0	-67	-100	-100
PM	-100	-100	-67	0	0	-67	-100	-100
PB	-100	-100	-67	0	0	-67	-100	-100

Table 6.2 Enhancement Matrix for Counter Rudder

Equation 6.1 is now be modified to encompass the new EM features (equation 6.2).

$$fuzzy\_output_n = \min(+100, \max\left(\frac{(fuzzy\_error * \mathrm{RR}) + \frac{\mathrm{EM\_RR[a][b]}}{100}}{x} + \frac{(fuzzy\_rate * \mathrm{CR}) + \frac{\mathrm{EM\_CR[a][b]}}{100}}{y}, -100\right)) \tag{6.2}$$

where:

EM_RR = Enhancement matrix for rudder ratio

EM_CR = Enhancement matrix for counter rudder

a = Fuzzy sets representing the fuzzified input of rate of change of heading error for the n^{th} output set

b = Fuzzy sets representing the fuzzified input of heading error for the n^{th} output set

Since each EM can contain both positive and negative numbers, in addition to coping with on-line gain requirements to meet dynamic alterations or environmental conditions, the EMs may be modified by the SOC to increase gains when they are set too low by the mariner, or conversely to decrease gains when they are set too high.

Having established the function of the two EMs, it is important to realise that vessel performance will only be satisfactory if the contents of each EMs is correct. In order to ensure that the EMs are capable of correct operation, the performance indices are employed. Observations of the vessel performance are passed to the performance index in terms of the fuzzified heading error and fuzzified rate of change of heading error. Based on these observations, the performance index can enforce any required modifications to each EM. The ability of the SOC to achieve the correct modifications to the EMs is fundamental to the its successful operation and is therefore dependant upon the content of the performance index utilised.

6.5 PERFORMANCE INDEX DEVELOPMENT

Other SOC applications cited in section 6.2, have employed a single performance index (PI) to adjust their individual fuzzy rulebase. Now that the rulebase has been replaced by a pair of EMs, it is necessary to develop two corresponding PIs, one being applicable to the EM for rudder ratio, the other for the counter rudder EM.

In both cases the PI design was based upon the traditional structure with the inputs being derived from the fuzzified heading error and rate of change of heading error information. The content of the PIs was set to zero for acceptable performance levels so that no change to the either enhancement matrix would result. When the performance level observed from the input data appeared to represent an aggregate gain being too high, then a negative PI value was set, thus reducing the enhancement matrix value identified, and therefore generating a reduction in the aggregate gain. Similarly, for low performance levels, then the PI value was set positive to induce an increase in the enhancement matrix value and a subsequent increase in aggregate gain. The PIs for rudder ratio and for counter rudder are given below (Tables 6.3 and 6.4).

Rate\Error	NB	NM	NS	NT	PT	PS	PM	PB
NB	+2.0	+0.7	-0.3	-1.0	-1.0	-0.8	-0.5	0.0
NM	+1.6	+0.6	-0.1	-0.6	-0.6	-0.2	0.0	+0.5
NS	+1.2	+0.6	+0.1	-0.2	-0.2	0.0	+0.3	+0.8
NT	+1.0	+0.6	+0.2	-0.1	-0.1	+0.2	+0.6	+1.0
PT	+1.0	+0.6	+0.2	-0.1	-0.1	+0.2	+0.6	+1.0
PS	+0.8	+0.3	0.0	-0.2	-0.2	+0.1	+0.6	+1.2
PM	+0.5	0.0	-0.2	-0.6	-0.6	-0.1	+0.6	+1.6
PB	0.0	-0.5	-0.8	-1.0	-1.0	-0.3	+0.7	+2.0

Table 6.3 Performance Index for Rudder Ratio

Rate\Error	NB	NM	NS	NT	PT	PS	PM	PB
NB	-2.0	-1.6	-1.2	-1.0	+1.0	+0.8	+0.4	0.0
NM	-1.6	-1.2	-0.8	-0.6	+0.6	+0.2	0.0	-0.5
NS	-1.2	-0.8	-0.5	-0.2	+0.2	0.0	-0.4	-0.8
NT	-1.0	-0.6	-0.2	-0.1	-0.1	-0.2	-0.6	-1.0
PT	-1.0	-0.6	-0.2	-0.1	-0.1	-0.2	-0.6	-1.0
PS	-0.8	-0.4	0.0	+0.2	-0.2	-0.5	-0.8	-1.2
PM	-0.5	0.0	+0.2	+0.6	-0.6	-0.8	-1.2	-1.6
PB	0.0	+0.4	+0.8	+1.0	-1.0	-1.2	-1.6	-2.0

Table 6.4 Performance Index for Counter Rudder

The magnitude of each element in the respective PIs was determined based upon experience, observations and an understanding of the nature of the learning required and as such may be considered to be application dependant. Poor performances are penalised by large magnitude modifications to the respective EM responsible, whilst desirable performance levels generate no modification. Between these two extremes is a variety of permutations which reflect the non-linear set point positions in the fuzzy input windows. It is essential to take into account poor performances which are being modified correctly, e.g. PB heading error which is reducing at an NB rate of change of heading error is an acceptable performance. However why the PB heading error was present could be related to either earlier incorrect control, or due to disturbance effects.

When the sea conditions become rough it is unrealistic to expect the vessel's performance to be maintained with the same quality of response possible during calm conditions. Given that the only external indicators concerning weather, vessel performance are the heading error and the rate of change of heading error, then an element of uncertainty regarding the exact cause of any irregularities in performance will remain. Assumptions regarding the learning required for generalised performance conditions are therefore a firm basis to initiate the development of the PIs. The seven key assumptions utilised for this thesis are:

For heading error EM -

1. If heading error and rate of change of heading error are approximately zero, then decrease the gain enhancements slowly until a deterioration in performance is detected. Then increase them slightly to regain the previous performance level.

2. If heading error is NB with rate of change of heading error NB, or if heading error is PB with rate of change of heading error PB, then the performance is very poor and the RR EM values responsible are increased significantly.

3. If heading error is PB with rate of change of heading error NB, or if heading error is NB with rate of change of heading error PB, then the performance is very satisfactory and no modifications are required.

For rate of change of heading error EM -

4. If heading error and rate of change of heading error are approximately zero, then decrease the gain enhancements slowly until a deterioration in performance is detected. Then increase them slightly to regain the previous performance level.

5. If heading error is NB with rate of change of heading error NB, or if heading error is PB with rate of change of heading error PB, then the performance is very poor and the CR EM values responsible are decreased significantly.

6. If heading error is PB with rate of change of heading error NB, or if heading error is NB with rate of change of heading error PB, then the performance is very satisfactory and no modifications are required.

7. If the heading error is approximately zero, i.e. NT or PT, but the rate of change of heading error is NB or PB, then a medium size modification is required.

Having established these performance assumptions, it is possible to interpolate between to calculate the detailed contents of each of the PIs.

With the PIs designed, a relationship must be developed between the current performance levels observed and the enhancements in the EMs which require modification, to generate an improvement in response when activated in the future. This relationship is based on the time taken for the vessel to respond to controller demands and is therefore similarly to the delay in reward discussed in section 6.2.

6.6 TIME DELAY IMPLICATIONS

The nature of the time delay feature is related to the time constant of the vessel. The rationale is based upon reasoned logic that if an aggregate gain value is utilised now, then the vessel will take a finite time to respond to that control action. If the resulting performance level is unacceptable, then this is indicative of the aggregate gain being incorrect and hence adjustment of the EM is required. The lapse in time between action and response is complicated further by the fast sample time being used. Therefore, before the vessel has completed its response to the first control action, many other control actions will have been computed by the controller. Whilst some of these later control actions will be replications of the earlier ones, others will be new and therefore different, based on the changing controller inputs.

The importance of the time delay is reinforced when considering the nature of the learning process utilised by the SOC. If EM modifications are based on observed performance levels, then it is crucial to ensure that any future modifications of an EM element are based upon the performance level induced by the newly modified element and not derived from an old value which has already been subsequently adjusted. If not undertaken correctly, EM elements can be over-modified with a resulting poor, and possibly unstable, performance being obtained.

Traditional control theory states that as a rule of thumb, a system may be regarded as finishing its response to a control signal after five time constants (5τ) have elapsed, i.e. 99% complete. Unfortunately the response after 5τ becomes too obscured by later control actions making it difficult o determine the relevance of the performance level observed to any particular EM elements. Conversely, considering a time lapse of only 1τ (63% complete), although the vessel response is fully initiated, it has not been given sufficient opportunity to reach its final state of response. Thus to measure performance levels at this time can indicate the manner in which the vessel's performance is improving or deteriorating, but not the degree of that change. The delay in reward must be of a reasonable order, but need not be an exact value due to the high sample frequency being used for this application. Therefore, a reasonable compromise is to utilise a time delay of 3τ (95% complete), as this magnitude of time delay allows for vessel response whilst minimising the possibly conflicting responses induce by later control actions and conflicts with earlier work [6.9] which considered that less than 1τ proved the most suitable value. The difference between these findings is due to the applicational considerations. This study is aimed at small vessels, with the emphasis on course-keeping. The work by Sutton and Jess considered warship control and utilised learning from an empty rulebase over multiple course-changing manoeuvres. During course-changing the rudder actions are more definite with large rudders decreasing to small rudders. The scale of the potential over-lap of control actions is therefore reduced and the speed with which related performance levels may be clearly identified is thus increased.

The time constant must thus represent the entire composite time response of the vessel as a complete system, i.e. the time constant used must incorporate vessel dynamics and those of the steering system including the rudder. For details of the derivation of the time constant, please refer to section 7.3.

6.7 OPERATION OF THE SOC

Having defined the individual constituent parts of this new SOC, it is necessary to link them into a form of control methodology which is usable for this, and other, applications. The SOC learning works in parallel to the foundation FLC and consists of two main structures, these being the data storage mechanism and the modification routine (Figure 6.1).

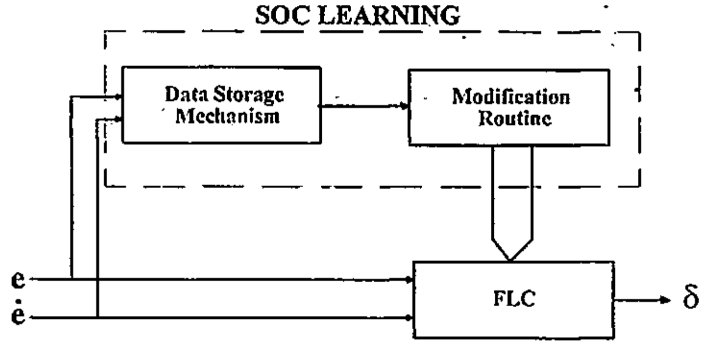

Figure 6.1 Block Diagram of SOC Layout

6.7.1 DATA STORAGE MECHANISM

The data storage mechanism is a means of recording which EM elements have been activated at a given sample time. This information is critical if the correct EM elements are to be modified, when the level of performance which they have induced has been observed. To minimise the necessary data storage requirements, this information was only retained at intervals of 6τ during course-keeping. When operating in the course-changing mode, the non-linear nature of the EMs is consistent with an improved course-changing response and there is no requirement for learning. This is because each change of course will cause different difficulties and there is therefore no rationale for employing the learning from an earlier course-change when undertaking a later one. Even should the environmental conditions have remained constant, the original course will be different and thus the need for higher or lower gains will have altered. In addition, learning from course-changing will be diffused by subsequent learning during course-keeping and any learning undertaken during course-changing may also cause a detrimental effect on the more sensitive and important operation of course-keeping. If learning in the course-keeping mode is correctly designed, then the vessel response within the critical ±10° will be assured for all modes of autopilot operation..

The data stored is based on the fuzzified inputs of heading error and rate of change of heading error at that sample point. Both inputs have been fuzzified into two fuzzy sets in the eight set range, each with an associated membership value. The EM elements are identified using the method previously applied to the fuzzy rulebase in Chapters 4 and 5, thus the data requirement for this operation includes the necessary information for inference (equation 5.11) to occur for each combination of input sets. Obviously the "min" function, when applied to the two greater membership values, will generate the most significant inferred EM membership component which is considered to be responsible for the subsequent performance level observed. Conversely, the "min" function when applied to the two smaller membership values can be considered to generate the least significant inferred EM membership and thus have lowest participation and thus a much reduced responsibility for the ensuing performance.

The data is thus stored in order of importance with the greater inferred membership value and associated fuzzy input sets first, and the smallest inferred membership value and associated fuzzy input sets last.

6.7.2 THE MODIFICATION ROUTINE

The modification routine must not be activated until a period of time equal to 3τ after the data storage mechanism has been activated to allow for the performance level observed to be related to the data stored. Similarly, once a correction has been undertaken by the modification routine, then a further period of 3τ must elapse before the next iteration of the learning process may commence, i.e. data storage, so that any new modifications to the EMs will be taken into account before learning continues. Therefore the modification routine also operates with a time period of 6τ, but is 3τ out of phase with the data storage mechanism.

Observation of the current performance level is achieved by utilising the fuzzification for heading error and rate of change of heading error which is valid when the modification routine operates. During the modification routine, four EM alterations are calculated, one for each combination of the current fuzzy input sets. In each case the alteration is adjusted by the applicable membership value and then summed with the other three alterations so that an aggregate EM modification is obtained which reflects both the position and magnitude of the performance level observations. This routine is applied to rudder ratio by using the rudder ratio PI, and for counter rudder by using the counter rudder PI. In both case the PI values are given in terms of gains, and thus require conversion before application to the EMs which are described non-dimensionally in terms of percentage variations. Equations for the respective modifications are given, (equations 6.3 and 6.4):

$$\mathrm{Mod\_RR} = \frac{\sum_{n=1}^{4}(\mathrm{PI\_RR}[\mathrm{Rate(set)}^n][\mathrm{Error(set)}^n] * \min(\mathrm{Rate}(\mu)^n, \mathrm{Error}(\mu)^n))}{\mathrm{RR} * \sum_{n=1}^{4} \min(\mathrm{Rate}(\mu)^n, \mathrm{Error}(\mu)^n)} \tag{6.3}$$

$$\mathrm{Mod\_CR} = \frac{\sum_{n=1}^{4}(\mathrm{PI\_CR}[\mathrm{Rate(set)}^n][\mathrm{Error(set)}^n] * \min(\mathrm{Rate}(\mu)^n, \mathrm{Error}(\mu)^n))}{\mathrm{CR} * \sum_{n=1}^{4} \min(\mathrm{Rate}(\mu)^n, \mathrm{Error}(\mu)^n)} \tag{6.4}$$

where:

Mod_RR	= Modification to the EM for rudder ratio
Mod_CR	= Modification to the EM for counter rudder
PI_RR	= Performance index for rudder ratio
PI_CR	= Performance index for counter rudder
set	= fuzzy sets describing heading error and rate of change of heading respectively
μ	= fuzzy membership for sets describing heading error and rate of change of heading respectively

The various combinations for the fuzzified input sets for n in the range 1 to 4 are described in Table 6.5, where set "a" is the set with the largest membership value, and set "b" is the one with the next to largest membership value.

n \ set	Heading Error	Rate of Change of Heading Error
1	a	a
2	a	b
3	b	a
4	b	b

Table 6.5 Input Set Combinations

The performance level observed, and hence the PI values utilised and the modification calculated, are based on the fuzzified inputs at the sample time when the modification routine operates. The EM elements to be modified are located by the information stored by the data storage mechanism and relate to the position within the EM of the elements which were used to generate the current performance. The observed performance level was caused by the activation of up to four EM elements from each EM, therefore up to four EM elements from each EM must be modified. Only one composite modification value has been generated for each EM, which reflects all of the associated membership values utilised by the EM activation. However, it is necessary to relate this modification value to the actual membership value of the EM element to be modified, before that modification takes place. This is to ensure that the scale of the modification is related to the responsibility of that element for the observed performance level. The EM modification must therefore be adjusted to allow for the significance of the element to be modified, equations 6.5 and 6.6.

$$\mathrm{Mod\_RR} = 2 * z * (\mathrm{Mod\_RR} * \min(\mathrm{Rate}(\mu), \mathrm{Error}(\mu))) \qquad (6.5)$$

$$Mod\_CR = 2 * z * (Mod\_CR * \min(Rate(\mu), Error(\mu))) \tag{6.6}$$

where:

z = Scaling factor.

The magnitude of each of the calculated EM modifications assumes an even distribution of responsibility, i.e. all minimum input memberships are 0.5. It is therefore necessary to scale the modification by a factor of two to maintain the significance of the calculated modification. In practice, the membership values are likely to be varied, thus for a inferred membership of 1.0 then double modification would result which would correspond to the strength of responsibility incurred, whilst a negligible modification would be allowed for a membership value approaching zero.

After establishing the final modification for each identified component in both EMs, the alteration of the relevant values is effected by equations 6.7 and 6.8.

$$EM\_RR[Rate(set)][Error(set)] = EM\_RR[Rate(set)][Error(set)] + mod\_RR \tag{6.7}$$

$$EM\_CR[Rate(set)][Error(set)] = EM\_CR[Rate(set)][Error(set)] + mod\_CR \tag{6.8}$$

By repeating equations 6.7 and 6.8 for each combination of input sets stored by the data storage routine, then up to four elements of each EM will be modified during each run of the SOC learning. However, it remains necessary to impose the restrictions of over-rules to ensure that the learning achieved remains correct.

6.7.3 THE APPLICATION OF OVER-RULES

After translating from rulebase usage to that of the enhancement matrix, not all of the original over-rules remain valid for this application. Each over-rule is therefore considered in turn to assess its individual validity.

Over-rule 1. Since there are no sets to specifically define the zero condition due to the eight set input window, it is not possible to ensure zero output for zero input by an over rule. However, the symmetrical nature of the EM will create this condition due to the retention of rule 4.

Over-rules 2 & 3. Due to the EM containing gain enhancements not rules, the symmetrical components of each EM have the same sign convention compared to the traditional rulebase used in the original foundation FLC where the sign convention was mirrored to obtain the desirable control. Thus to state that zones of the EMs should be positive or negative in nature will not facilitate learning.

Over-rule 4. The need to ensure that the EM stays symmetrical remains applicable to this application. Whilst the original reasoning for use with a zone of influence is irrelevant since such a zone is not being utilised, controller output must equate to a balanced operation with the integral action coping with any deterministic requirements. Thus which ever rule is modified, then its symmetrical location in the EM is also modified by the same amount.

Clearly of the four Sugiyama over-rules, only rule 4 may be utilised for this new SOC design. However, to meet the requirements of this application, five new over-rules were demanded, these are:

Over-rule 1. When more than one modification of the same EM element will occur is a single iteration of the learning cycle, then only the modification with the largest membership value should be used, i.e. the most significant modification. This rule avoids excess and incorrect learning.

Over-rule 2. No negative gain enhancement should exceed the value of the variable gain setting as adjusted by the mariner. This rule avoids the concept of negative aggregate gains. In practice, there is no justification for reducing the aggregate gains below zero, however unpredictable control could result if this were to occur.

Over-rule 3. No learning is required during course-changing mode. This rule avoids unnecessary learning which has little impact on course-changing but could impose a detrimental effect on the course-keeping abilities of the controller.

Over-rule 4. No learning is required within the initial one hundred and twenty seconds of course-keeping to allow the integral action time to reduce any steady-state error. This rule avoids learning about apparently poor performance which will be corrected automatically.

Over-rule 5. During learning, no modification is required to the EM elements associated with either NB or PB heading errors, irrespective of the rate of change of heading magnitude, as any such alterations will have little influence upon the course-keeping performance, but may seriously impair the course-changing abilities.

6.8 ON-LINE TRIM ADJUSTMENT

The concept of the SOC learning for on-line adjustment of the rudder ratio and counter rudder gains has been described. However, for the final controller design to be able to operate independently of the mariner, it is necessary to ensure that the integral gain (trim) is also set up with a suitable value. This routine can be considered as independent of the main learning mechanism. However, similarly to the previously described method of learning, the trim adaption should not occur during course-changing, or for the initial period of course-keeping to allow the vessel an opportunity for the integral action to take effect.

The magnitude of the average heading error indicates the success of the integral action with the current trim setting, since the integral action is intended to remove any such steady-state error. The trim adaption is therefore based upon the average heading error generated from equation 6.9. This value is then utilised in its absolute form because the trim value must be incremented, or decremented, due to the magnitude of any heading error, not in respect of any sign differences.

$$fuzzy\_abs\_ave\_error = \mathrm{abs}\left(\frac{\sum_{0}^{n} fuzzy\_error}{n}\right) \tag{6.9}$$

where:

fuzzy_abs_ave_error	= Averaged heading error at the n^{th} sampling absolute form
fuzzy_error	= Fuzzified heading error
n	= Number of samples

The trim adaption remains a crude mechanism in comparison to the detail for rudder ratio and counter rudder. In practice the trim gain is less sensitive to incorrect tuning and operates in a more uniform manner across the operating envelope. Thus there is no need for delicate refinement. Table 6.6 summarises the rules utilised for the trim adaption.

The trim adjustment can then be added to the trim variable set by the mariner. When the steady state heading error is greater or equal to ±3°, the trim setting is incremented by 0.5. Similarly it is incremented by 0.1 for errors in the range ±0.45° to ±3°.

Fuzzified Abs Error	**Fuzzified Abs Rate**	**Trim Gain Adjustment**
≥20	N/A	+0.5
≥3 & <20	N/A	+0.1
<3	>50	-0.5
<3	>16 & <50	-0.1

Table 6.6 Rules for Trim Adaption

Steady state error less than ±0.45° may be consider negligible, unless a rate of change of heading error is observed. When this rate is greater than ±1.0°s^{-1} the trim setting is decreased by 0.5, and by 0.1 when the rate is in the range ±0.3°s^{-1} to ±1.0°s^{-1}.

Trim adaption is carried out at intervals of 6τ to correspond to the main learning mechanism, and thus operates in phase with the modification routine. Learning for rudder ratio and counter rudder is retained within the autopilot during both operation and standby (autopilot on but not engaged) periods since any improved performance derived from learning is likely to remain valid. In the case of the trim adaption, any modification will be course dependant and thus the calculated modification is set to default when in standby mode to prevent a subsequent loss of performance.

6.9 CONSIDERATION OF THE NEW SOC DESIGN

A new design of SOC has been created for the small vessel application which was based on the Sugiyama algorithm's performance index and over rule features.

The rulebase was replaced by two enhancement matrices, one for rudder ratio and the other for counter rudder. Each EM contained detail of how the gain should be enhanced for a given set of inputs (heading error and rate of change of heading error). Instead of an empty rulebase, the EM was designed to include basic ship control information and the non-linear effects developed for the earlier rulebase. The use of the EMs allowed the SOC to work with variable gain settings from the mariner. In addition it allowed a clear distinction between rudder ratio and counter rudder so that the learning mechanism could enforce more precise changes in gain than was possible using the rulebase. Performance indices were also developed to operate in conjunction with the EMs. Learning was carried out in two stages, the data storage mechanism and the modification routine. Each were separated by 3τ where τ was determined to be the overall time constant representing both the ship dynamics and those of the steering mechanism. Trim adaption was carried out simultaneously with this learning, however a series of over rules was developed to ensure that the learning was correctly achieved.

The nature of the final SOC design differs greatly from any others, including previous marine applications. This is mainly due to the need to resolve the strict requirements imposed by this particular application. However, it is only by full scale sea trials that any new design can be validated, thus proving that its potential.

6.10 REFERENCES

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CHAPTER 7. VALIDATION OF THE AUTOPILOT DESIGN

7.1 INTRODUCTION

In this thesis a new design of autopilot has been developed and presented in detail. With any theoretical research, true credibility can only be established when the final design is seen to perform in its real operating environment. For this work, a fully functional autopilot was therefore be embedded within the "autopilot system" described in Appendix A. The system was then be installed on a physical vessel of typical size and type so that a range of representative manoeuvres could be undertaken, with the results logged on a computer system for subsequent analysis. For this application it was decided that the essential data to record would be time (s), desired heading (°), actual heading (°), yaw rate ($°s^{-1}$) and actual rudder (°), all with a sample period of 0.1 seconds.

In order to demonstrate the success, or otherwise, of the controller design, it was fundamental that a comparison be made to an alternative source of data. The hypothesis presented within this thesis is that a FLC may be designed to outperform the conventional PID autopilot. With the addition of the learning elements, the FLC was transformed into the SOC which then further enhanced the performance advantage. Since the new design of autopilot is to succeed the conventional PID controller, then it is a pre-requisite of any validation, that PID data was also obtained for the identical sequence of manoeuvres so that a comparative study of the two applied methodologies could be undertaken. Clearly since the full scale trials were undertaken at sea, because of the variable nature of wind, waves, tide and current, the precise repetition of environmental conditions is impossible. Only by testing the two controllers sequentially, with a minimum of delay between experimental runs, could continuity of conditions be approached. Whilst not ideal, this is the most realistic form of testing possible for this application. The alternative approach would be scale model testing in a controlled environment, e.g. a manoeuvring tank. With model testing, significant functions of the autopilot may

Being of suitable size, speed and displacement, this vessel was typical of the various types which currently operate the conventional autopilot system and was therefore considered as ideal for validation testing. In accordance with the description of the autopilot variables (Appendix A), the settings for these tests are shown in Table 7.1.

Variable Name	**Variable Setting**
RR	6
TRIM	4
CR	3
RDB	1
MRA	9

TABLE 7.1 AUTOPILOT SETTINGS UTILISED FOR SEA TRIALS

With the exception of the MRA variable, these settings are typical, and therefore a good standard of performance may be expected from the conventional PID autopilot in both course-keeping and course-changing modes of operation. However, no attempt has been made to optimise these variables either for the vessel, or for the environmental conditions. In must be recognised that by using such variable values, the testing is more realistic of normal autopilot operation whilst also providing the SOC with limited scope to carry out any learning deemed necessary. The MRA variable was set to 9 which represents ±30°, the limits of the working range of the rudder on this vessel. The settings in Table 7.1 were utilised for the conventional PID, FLC and SOC tests without any adjustment taking place. All the controllers therefore had the same gain settings and were tested in near identical sea conditions. Any variations in results can therefore be considered as being due to the nature and ability of the individual controller and not the result of any outside factors or influences.

Test were carried out with the engines at 2100 rpm which equated to 18 knots. By maintaining this speed for the tests it was possible to ensure that the vessel remained in the planning mode so that any incorrect rudder demands would be more noticeable due to the increased responsiveness of the vessel's dynamics.

Sea and wind conditions were light and could be associated with those described by sea state 3. The prevailing wind direction was 101°. These tests were carried out during the morning with low tide at 08.49 at a height of 0.87m. Although of less significance then the wind, the tidal effects would have operated in a similar direction, their magnitude modestly increasing during the trials once the tide had "turned". Wave, wind and tidal effects would therefore have been present when undertaking these tests, however, being disturbance effects of characteristic magnitude, their effect on the vessel's performance should have been acceptably within the range permitted for autopilot use on small vessels of this type.

7.3 TIME CONSTANT DERIVATION

As described in section 6.6 the SOC required a time delay feature for the learning mechanism, which was related to the time constant of the vessel. For these validation sea trials, an experimental approach was utilised to obtain a good approximation of this value, however an alternative approach would be to develop a set-up test program which could be run once by the installation engineer, and which would calculate the required time constant value by carrying out a pre-defined series of manoeuvres.

The rudder was forced to is its maximum physical limit, this ensured that the vessel would turn with the largest possible yaw rate. Figure 7.2 shows the rudder response obtain for this operation and it is apparent that whilst the autopilot limits are ±30°, the physical limits are a little greater at ±32°. The difference is to prevent the autopilot from generating rudder demands which are large enough to encounter the physical stops at the limits of the rudder 's range of movement. Such an occurrence would slowly induce undesirable, and unnecessary, wear on the rudder system. This limiting feature is commonplace on most small vessel autopilots.

As the rudder angle increases, then the vessel will begin to turn. However, the final rate of turn (yaw rate) is determined by the magnitude of the rudder angle. Thus when the rudder reached the maximum physical limit of about 30°, the vessel approached a constant rate of turn, which was found to approximate to -7.6°s^{-1}, and was reached about 4.6 seconds after the vessel's turn began (Figure 7.3).

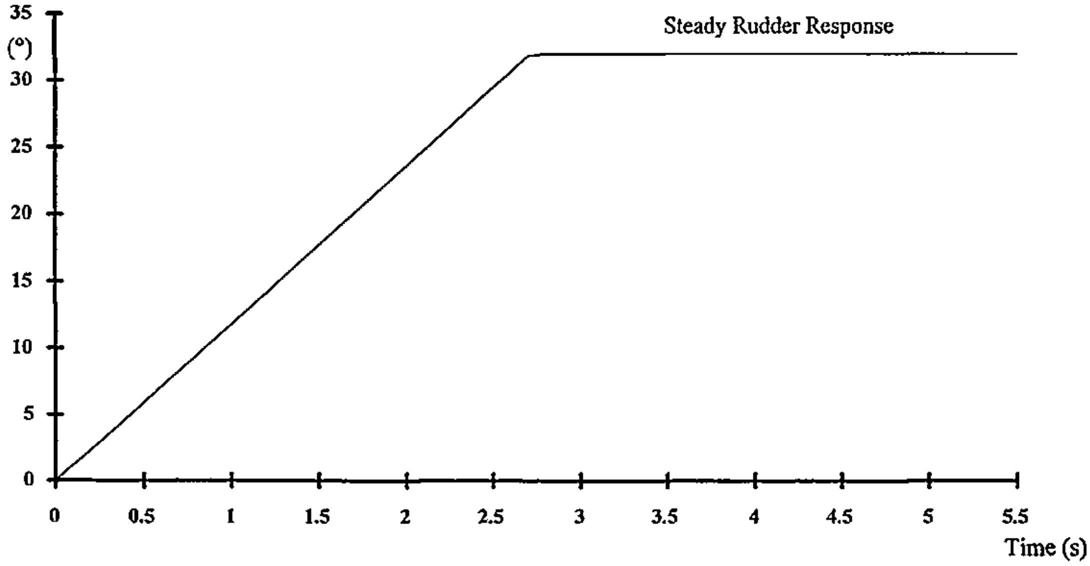

Figure 7.2 Rudder Response for Time Constant Derivation

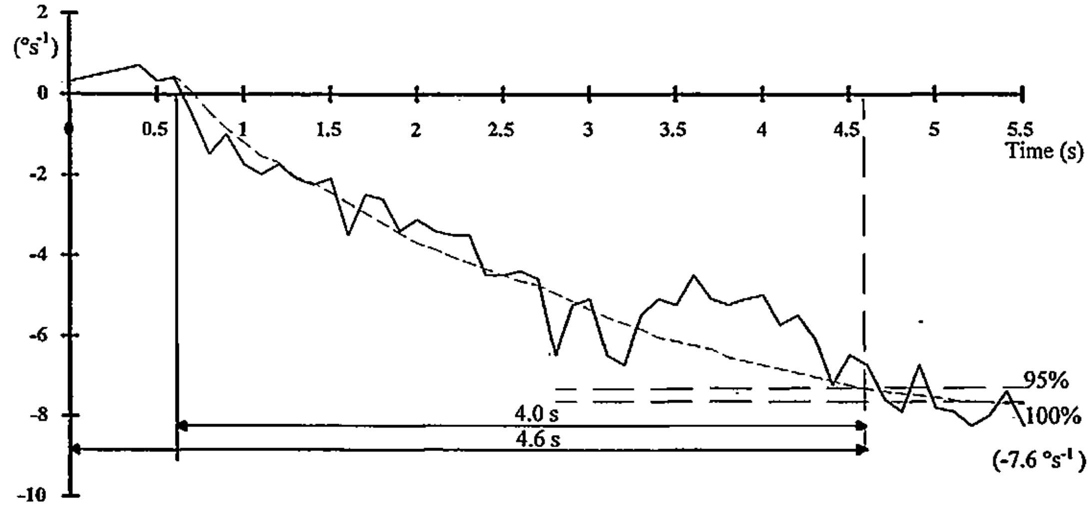

Figure 7.3 Yaw Rate Response For Time Constant Derivation

If the vessel is considered to have reached 95% of the steady-state response of -7.6°s^{-1} in 4.0 seconds (3τ), then the time constant for just the vessel (τ) must approximate to 1.33 seconds. However, it can be seen from Figure 7.3 that due to the time delay associated with the rudder mechanism, the composite time delay of the vessel when considered as a complete system, i.e. including time delay components for both the vessel and the steering mechanism, then 95% of the final yaw rate was achieved after 4.6 seconds (3τ). The value of time constant used for these tests was therefore 1.533 seconds.

7.4 VALIDATION OF THE FLC FOR COURSE-CHANGING

The problem regarding course-changing with the conventional PID controller, as discussed in section 2.2.3, is that the gain settings used are those for the mode of course-keeping and consequently are relatively low. The resulting course-changing ability is therefore inhibited and slow. Should the rudder ratio value be increased, then the course-change would be faster but would probably overshoot the desired heading. The higher rudder ratio, when subsequently applied to course-keeping, would generate a poor level performance. The non-linear FLC was designed to overcome this problem and utilises high rudder ratio and low counter rudder for large heading errors, whilst maintaining an equivalent response to the PID for close to the desired heading. To validate this, both large (90°)and small course-changes (30°) were demanded using both the FLC and PID controllers. The results of the rudder and heading response for the FLC and PID autopilots are shown in Figures 7.4 to 7.7. However, Figure 7.8 combines the heading results for both FLC and PID responses and the fundamental differences for the 90° change, and conversely the similarities for the 30° change, are clearly visible. Once the system was allowed to settle on a course of 90°, the course-changing tests consisted of a 90° course-change, followed by a subsequent 30° course-change after 140 seconds had elapsed.

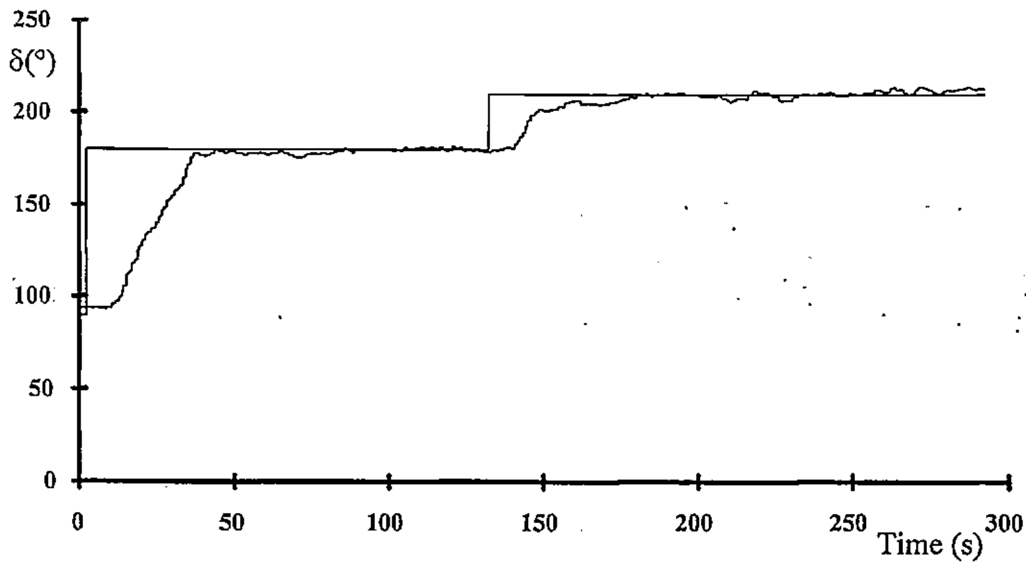

Figure 7.4 Heading Response for FLC Autopilot During Course-Changes of 90°, Followed by 30° after 140 Seconds

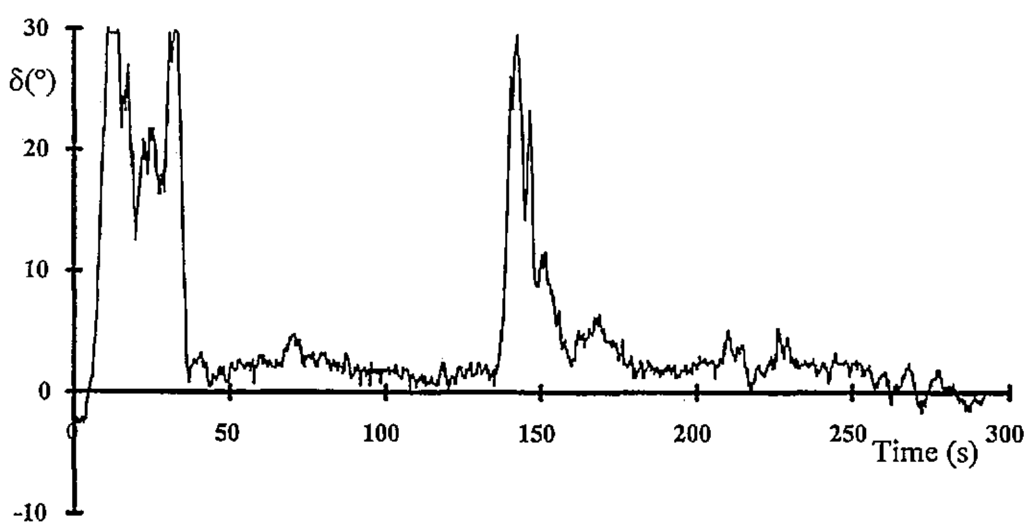

Figure 7.5 Rudder Response for FLC Autopilot During Course-Changes of 90°, Followed by 30° after 140 Seconds

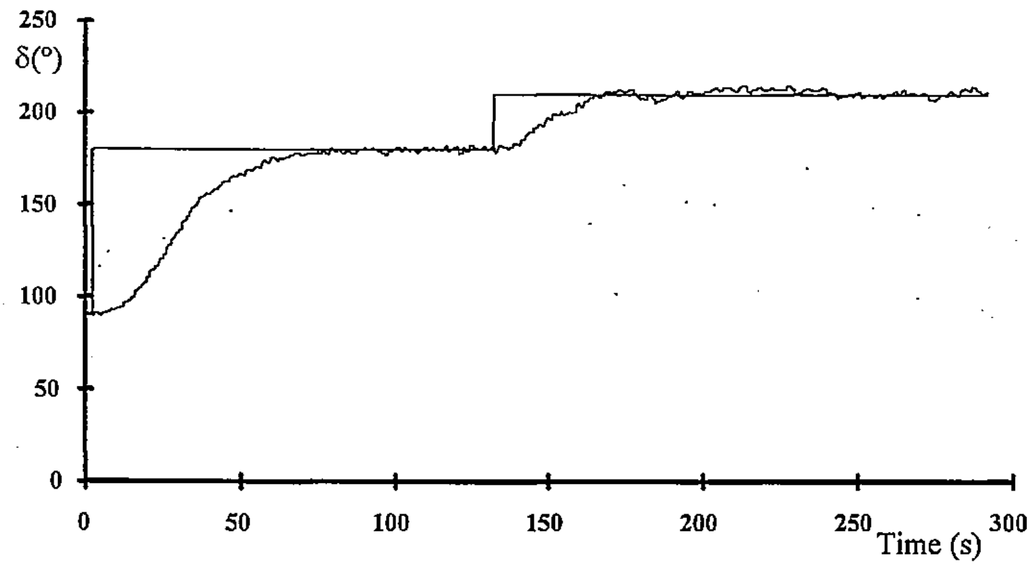

Figure 7.6 Heading Response for PID Autopilot During Course-Changes of 90°, Followed by 30° after 140 Seconds

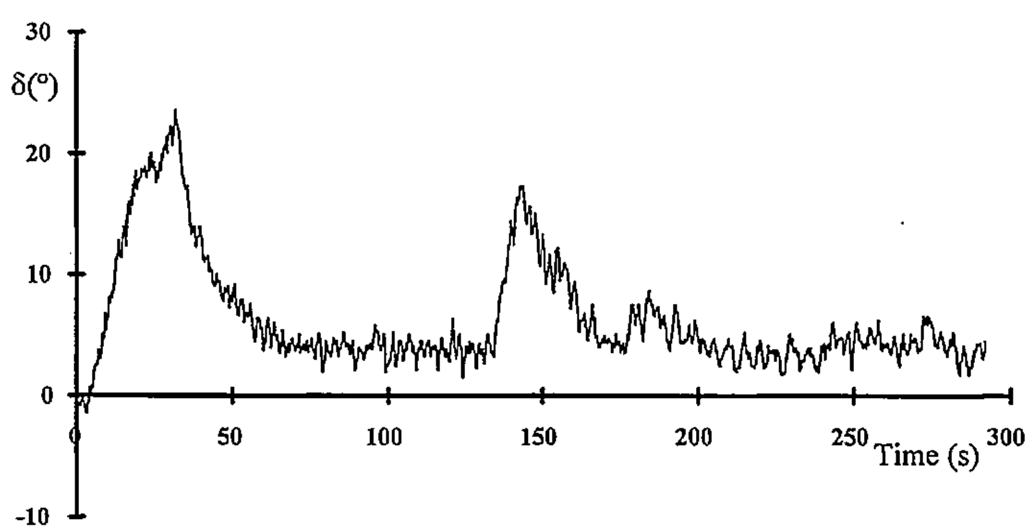

Figure 7.7 Rudder Response for PID Autopilot During Course-Changes of 90°, Followed by 30° after 140 Seconds

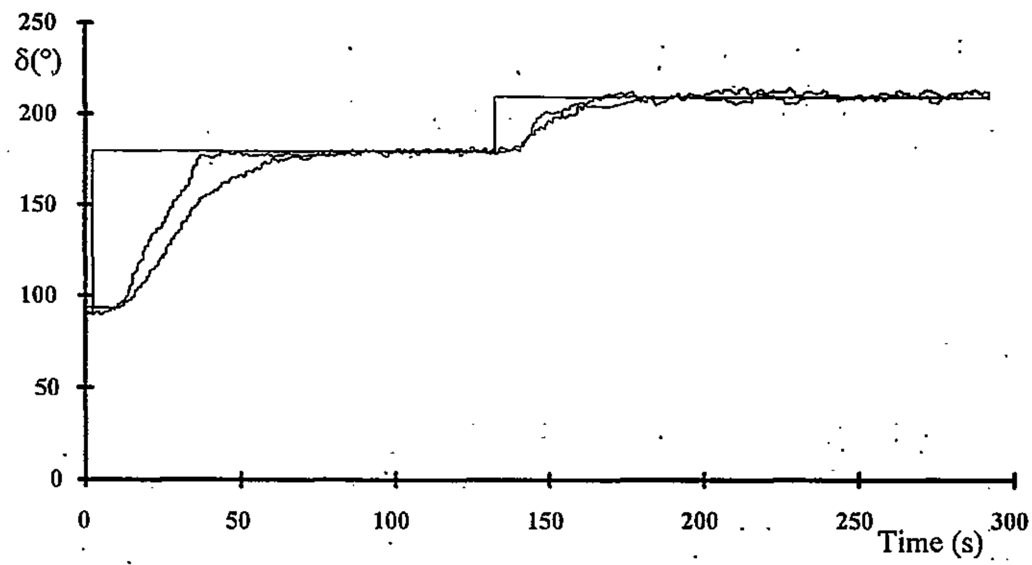

Figure 7.8 Combined Heading Responses for FLC and PID Autopilots During Course-Changes of 90°, Followed by 30° after 140 Seconds

7.4.1 DISCUSSION OF THE FLC COURSE-CHANGING RESULTS

The quality of the actual course change in each case was measured in terms of vessel heading by:

1. Rise Time - the time taken for the vessel heading to respond to the new course demand and is defined as the time for 95% of the desired heading to be obtained.

2. Overshoot - the magnitude of the first overshoot of the desired heading.

3. Settling Time - defined as the time taken for the response, after a course change demand, to settle within ±2° of the desired heading.

Details of the results obtained for these tests are given in Table 7.2. The FLC's performance is related to that of the PID autopilot by calculating the performance difference as a percentage of the PID result.

	Course Change	PID	FLC	FLC/PID %
Rise Time (s)		62.0	33.6	-46
Overshoot (°)	90°	0	0	0
Settling Time (s)		95.3	78.7	-17
Rise Time (s)		59.9	84.2	+24
Overshoot (°)	30°	+2	0	-100
Settling Time (s)		68.8	59.8	-13

<u>Table 7.2 Heading Results FLC and PID Course-Changing</u>

Similarly, rudder activity was measured in terms of root mean square (RMS) values, maximum movement and range of activity (Table 7.3).

	PID	FLC	FLC/PID %
RMS Rudder (°)	6.36	4.73	-26
Maximum Movement (°)	23.65	30.00	+27
Range of Activity (°)	25.12	32.71	+30

<u>Table 7.3 Rudder Results FLC and PID Course-Changing</u>

Considering the 90° course-change, a fast improvement in heading response is observed in Figure 7.4 with the rise time drastically reduced by 46% as a result of the non-linear effects incorporated in the FLC autopilot. Once close to the desired heading, the FLC then operates similarly to the PID controller, and there is no overshoot. When in progress this FLC course-change was not observed to induce excessive roll in the vessel and thus the "passenger ride" remained comfortable. In addition, the FLC rudder response shown in Figure 7.5 is much more positive than that of the PID alternative. For course-keeping the small rudder movements are completely ineffective until the vessel heading approaches the desired heading. Thus the FLC, without the small rudder movements for the first section of the response, can be considered to generate less rudder wear and also consequently would result in a lower power consumption in comparison to the PID.

The vessel heading performances obtained for each autopilot, for the 30° course change, were very similar to each other, this was expected due to the non-linear FLC design Both responses rose and settled quickly although the PID was found to overshoot by 2°, possibly as a result of noise, whilst the FLC rose significantly faster, but was a little slower at settling and did not overshoot the desired heading. In order to achieve this improved response the FLC utilised a much larger range of rudder values. However, it is important to note that the RMS rudder for the FLC is actually 26% smaller than that of the PID controller. Since the magnitude of the RMS value is an indication of the size of the dynamic forces induced on the vessel by the rudder action, the FLC rudder response clearly has reduced these influences by approximately one quarter. addition, the RMS value is a measure of the rudder power utilised, therefore the required power was also reduced by 26%.

7.5 VALIDATION OF THE FLC FOR COURSE-KEEPING

During the course-keeping mode of autopilot operation, the difficulty is to minimise the heading error without allowing the rudder activity to become too significant. The non-linear FLC autopilot was designed to perform similarly to the PID controller for small heading errors. As the heading errors increase, then the same higher rudder ratio values utilised during course-changing begin to become active and thus force the vessel heading back on course. A narrow band of acceptable

performance can therefore be created in which the vessel heading will be maintained To validate this hypothesis regarding the FLC's course-keeping properties, the vessel was allowed to settle on a heading of 260°. For each controller, a two hundred and thirty second course-keeping test was then undertaken to maintain the heading of 260°.

7.5.1 DISCUSSION OF THE FLC COURSE-KEEPING RESULTS

Vessel heading and rudder results were recorded for both the FLC and the PID autopilots and results are shown in Figures 7.9 to 7.12. For course-keeping operation, heading and rudder data were analysed using RMS values, maximum values, minimum values, range of activity, variance and standard deviation (Tables 7.4 and 7.5).

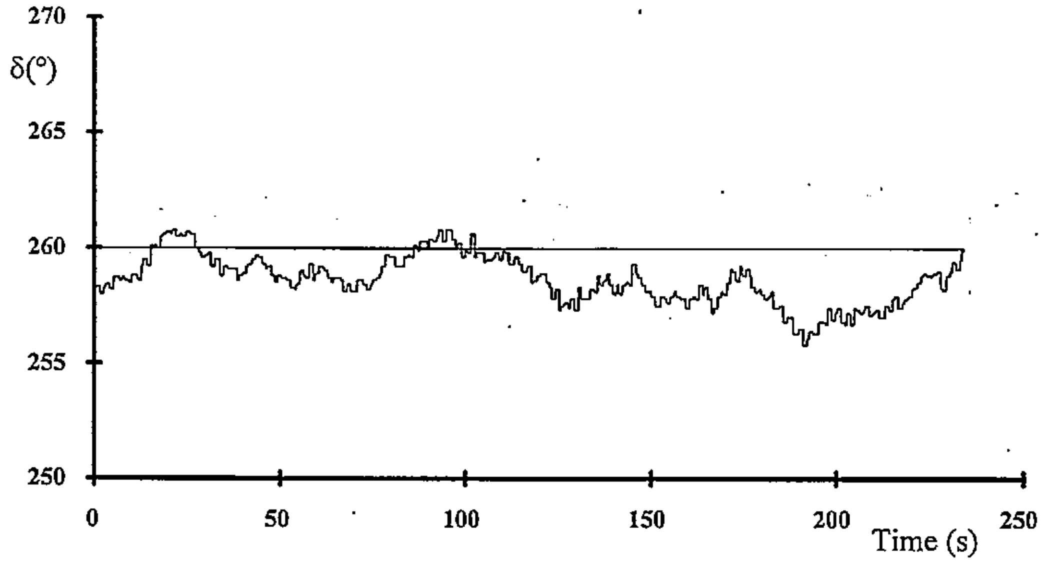

Figure 7.9 Heading Response for FLC Autopilot During Course-Keeping with a Desired Heading of 260°

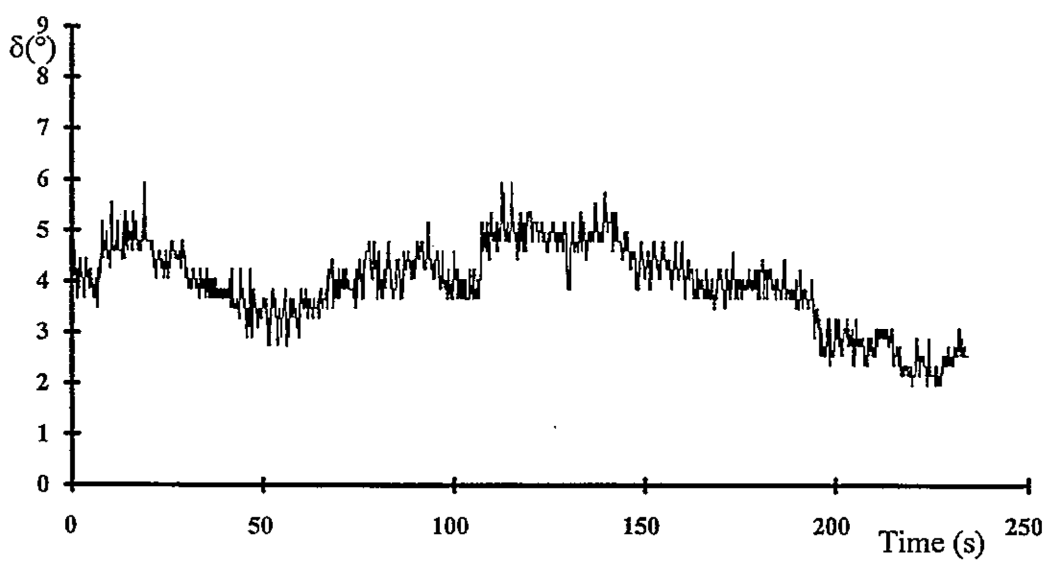

Figure 7.10 Rudder Response for FLC Autopilot During Course-Keeping with a Desired Heading of 260°

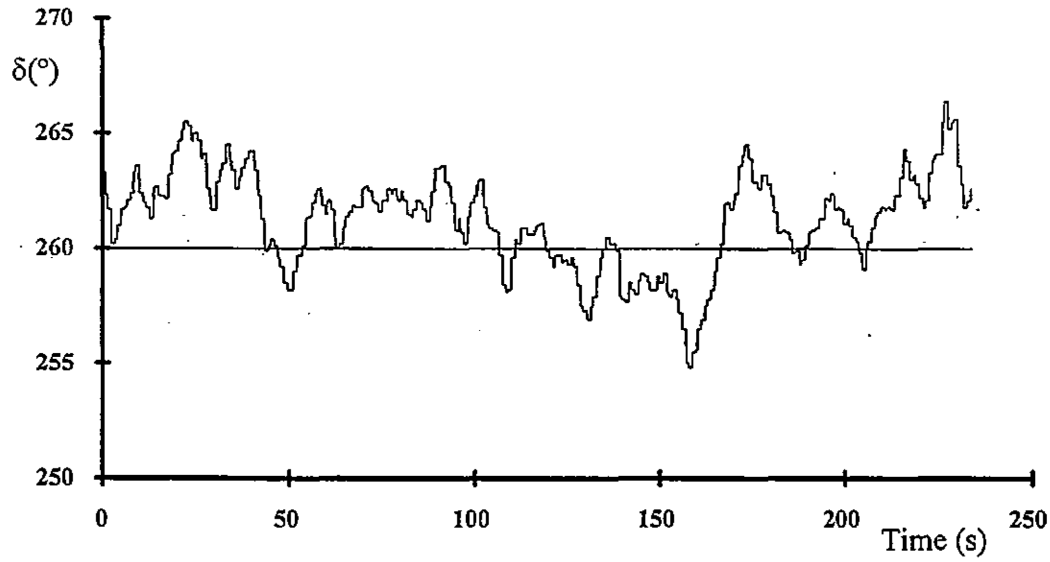

Figure 7.11 Heading Response for PID Autopilot During Course-Keeping with a Desired Heading of 260°

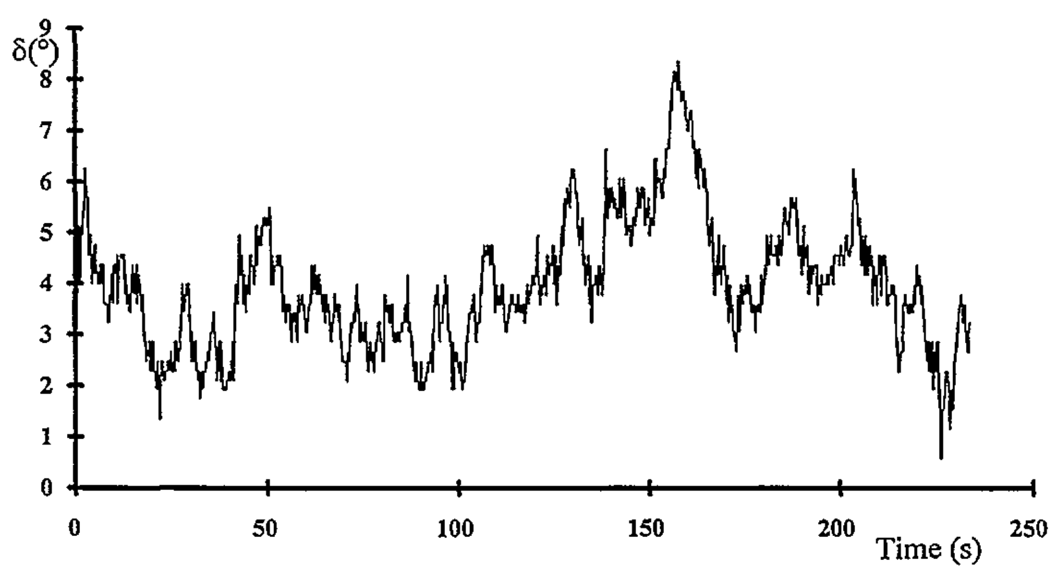

Figure 7.12 Rudder Response for PID Autopilot During Course-Keeping with a Desired Heading of 260°

	PID	FLC	FLC/PID %
Maximum Error (°)	6.4	2.0	N/A
Minimum Error (°)	-5.2	-3.7	N/A
Range of Error (°)	11.6	5.7	-51
Variance	4.4	2.0	-55
Standard Deviation	2.1	1.4	-33

N/A = Not Applicable

Table 7.4 Heading Results FLC and PID Course-Keeping

	PID	FLC	FLC/PID %
Maximum Movement (°)	8.4	5.9	N/A
Minimum Movement (°)	0.6	1.9	N/A
Range of Activity (°)	7.8	4.0	-49
Variance	1.5	0.9	-40
Standard Deviation	1.2	1.0	-17

N/A = Not Applicable

Table 7.5 Rudder Results FLC and PID Course-Keeping

When considering the FLC's heading response in Figure 7.9, it is apparent that the hypothesis presented is true in that the vessel's heading remains much closer to the desired heading at all times due to the operation of the non-linear control strategy. This feature of the FLC, during course-keeping is reflected by the improvements of 33% for standard deviation and 55% for variance verifying mathematically the visual impact of Figure 7.9 when compared to Figure 7.11. Because the course

deviations are smaller, the passenger ride may also be assumed to be comparatively improved with a reduction in vessel roll which is induced by the corrective rudder action. With this improved course keeping, the down track time and therefore fuel costs, should be reduced considerable over the length of a voyage.

In both cases, the integral action has operated to reduce any steady -state error effects of the vessel's heading. Due to the constant variation of disturbance effects, to expect the integral correction to completely remove this error would be unrealistic. For the PID and the FLC autopilots, the absolute steady-state error was reduced to approximately 1°. However, it is interesting to note that for the PID controller the remaining error was positive, whilst for the FLC it was negative. This is not uncommon with small vessel autopilots and both results are within performance expectations and therefore equally acceptable.

The improved heading response from the FLC is due to an enhanced rudder action demanded from the controller. The FLC rudder response shown in Figure 7.10 demonstrates that the large rudder movement of the PID controller was replaced by a tight and effective rudder action. Because the rudder movements became far smaller, with the FLC, the variance and standard deviation are reduced by 60% and 34% respectively, and undesirable effects on vessel dynamics, induced by the rudder, will also have been significantly reduced. The occurrence of small rudder oscillations is apparent in the FLC's rudder response. However, these effects are acceptable since they appear with a similar frequency, but greater magnitude, to those found in the PID response. The improvement in control, due to these rudder movements, is apparent from the high quality of the FLC's heading response.

7.6 VALIDATION OF THE SOC FOR COURSE-KEEPING

Since the gain settings used for both the PID and FLC autopilots were not determined by any optimal design strategy, there is likely to be further improvement possible. In reality the performance of the of the FLC for both course-changing and course-keeping modes of operation has been far superior to the PID alternative. There is therefore no need for any radical controller adjustment, however, the requirement for further fine tuning still remains. Large degrees of learning are easy to facilitate with the SOC due to the construction of the PIs defined in Chapter 6. However, fine tuning has a far higher degree of complexity. Clearly, any incorrect learning will become immediately apparent as course-keeping qualities will suddenly begin to deteriorate. Conversely, any correct tuning will probably be of small magnitude, due to the original high performance level obtained, and thus not easily visible in the vessel's performance, but will occur as a gradual increase in performance over the duration of the validation test.

The validation test carried out was designed to compliment the previous FLC course-keeping test. Gain settings were initially determined to be those used previously for the FLC and PID autopilots. A desired heading of 260° was then maintained for a period of two hundred and thirty seconds with the resulting SOC responses shown in Figures 7.12 and 7.13. Since these tests were performed immediately subsequent to the previous PID and FLC validation tests, the environmental conditions may be considered to be as near identical as possible for this application. The results from this SOC test were therefore be compared to those of the FLC to identify any performance advantage gain resulting from the SOC's learning as a percentage. Similarly the SOC results were also compared to the original PID results to indicate the overall performance advantage achieved by the SOC autopilot

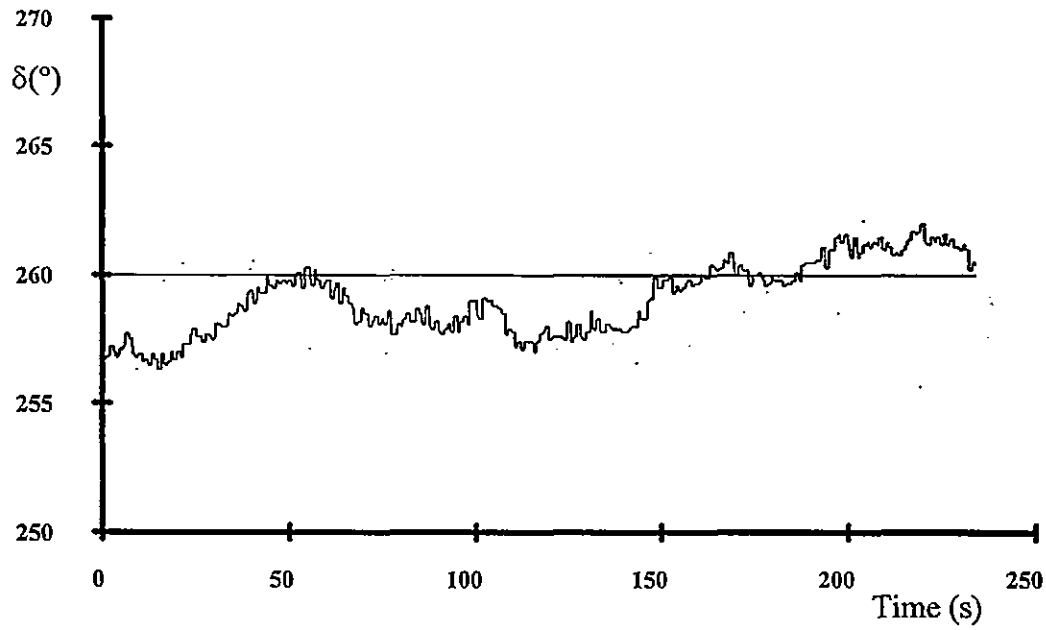

Figure 7.13 Heading Response for SOC Autopilot (Learning On) During Course-Keeping with a Desired Heading of 260°

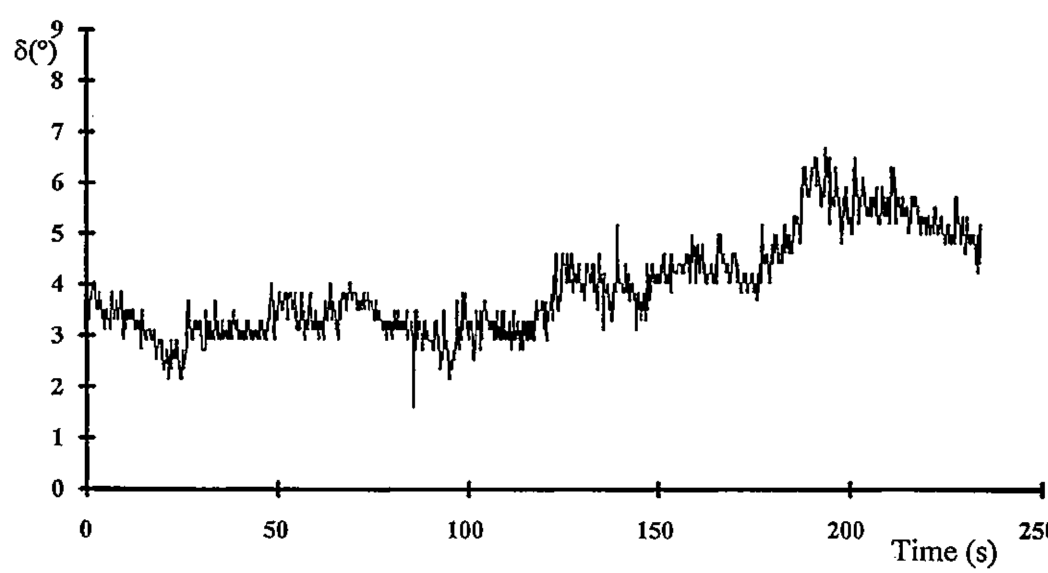

Figure 7.14 Rudder Response for SOC Autopilot (Learning On) During Course-Keeping with a Desired Heading of 260°

Because no learning occurs during course-changing, there was no advantage to undertaking any SOC testing in this mode of autopilot operation. Since the FLC was designed to merely be the SOC with its learning inhibited, the SOC's course-changing performance is that of the FLC and the results presented in section 7.3 are valid. For the same reasons, the FLC results for course-keeping are also those of the SOC when course-keeping with its learning turned off.

7.6.1 DISCUSSION OF THE SOC COURSE-KEEPING RESULTS

The results for vessel heading and rudder responses are shown in Tables 7.4 and 7.5 respectively with comparison, where relevant, made between the SOC and both the FLC and PID results to indicate the scale of learning imposed.

	SOC	SOC/FLC %	SOC/PID %
Maximum Error (°)	0.8	N/A	N/A
Minimum Error (°)	-4.2	N/A	N/A
Range of Error (°)	5.0	-14	-51
Variance	1.1	-45	-75
Standard Deviation	1.1	-21	-46

N/A = Not Applicable

Table 7.6 Heading Results SOC (Learning On) Course-Keeping

	SOC	SOC/FLC %	SOC/PID %
Maximum Movement (°)	6.7	N/A	N/A
Minimum Movement (°)	1.6	N/A	N/A
Range of Activity (°)	5.1	+28	-35
Variance	0.6	-33	-60
Standard Deviation	0.79	-21	-34

N/A = Not Applicable

Table 7.7 Rudder Results SOC (Learning On) Course-Keeping

Given the quality of the previous FLC course-keeping response, the results obtained for the SOC are quite significant. As expected, there were no dramatic alterations in the controllers performance. However, after an analysis of the data, it is apparent that considerable further learning has occurred with notable consequences. In particular, when considering the vessels heading response, in comparison to the high performance obtained by the FLC, the range of movement, i.e. the heading error, has been restricted by the SOC a further 14%. Both the variance and the standard deviation of this response have also been reduced by 45% and 21% respectively, . When compared to the original PID autopilot, these improvements for variance and standard deviation become 75% and 46%. The course-keeping ability of the SOC is therefore far superior to the PID controller and significantly better than the FLC. Since without learning in operation, the SOC and the FLC are the same controller, then this measured difference must be a reflection of the SOC's learning ability. It is therefore demonstrated that the SOC has the ability to learn on-line so that the vessel's performance may be improved to meet the relevant operational conditions.

Having investigated the heading performance, it is now necessary to consider that of the SOC's rudder response. Clearly, to obtain such major performance improvements must require an alteration in the rudder movement. In comparison to the FLC, the results in Table 7.5 indicate that the range of rudder movement has increased by 28%. This value still remains 35% lower than the range of movement utilised by the PID autopilot. However, it is important to note that despite the greater range of movement being used, the rudder's variance and standard deviation have been reduced a further 45% and 27% respectively compared to the FLC autopilot. When compared to the conventional PID alternative, these values are also similar at 40% and 17% respectively.

7.7 SIMULATED AUTOPILOT TESTING

The operation of the new autopilot design has clearly been demonstrated as a success, when installed on the sea trial test vessel. However, this self-organising autopilot is required to operate on a range of vessel types and it is therefore necessary to evaluate the likely performance obtainable on other vessel types. It was not practical to participate in further sea trials as no alternative test vessel was available. A study was therefore undertaken which utilised "PC" based Runge Kutta integration routine written in the computer language "C" to simulate a small vessel. The model used was a Nomoto model [7.1] of the form:

$$\frac{\varphi(s)}{\delta(s)} = \frac{K(1+sT_3)}{s(1+sT_1)(1+sT_2)} \tag{7.1}$$

where:

$\varphi(s)$ = Actual vessel heading.

$\delta(s)$ = Actual rudder position.

K = Gain term.

T_1, T_2, T_3 = Characteristic time constants of the vessel.

Rudder dynamics were modelled as a first order linear function with a time constant of one second and saturation limits of ±30°. The model utilised is of an 11.17m, 8500 Kg, vessel with a velocity of 4.5 ms^{-1}, and was derived from the hydrodynamic coefficients calculated by Burns *et al* [7.2]. However, by recalculating the relevant parameters, models were also derived for vessels of length 7.5m/mass 2572 Kg and length 15m/mass 20577 Kg (Table 7.8).

Length (m)	**Mass (Kg)**	K	**$1/T_1$**	**$1/T_2$**	**$1/T_3$**
7.5	2572	0.8536	2.467	0.577	0.898
11.17	8500	0.3848	1.656	0.388	0.603
15.0	20577	0.213	1.233	0.289	0.449

Table 7.8 Variations in Simulation Model Parameters

Details of typical disturbance effects applicable to small vessels are discussed in section 2.2.1. These disturbance effects for wind, waves and current were therefore utilised using data previously developed [7.2]. The autopilot settings remained identical to those described in section 7.2. Similarly, the relevant time constant values were calculated following the method discussed in section 7.3. The values used for this study were therefore 2.9 seconds (7.5m model), 4.0 seconds (11.17m model) and 4.8 seconds (15m model).

7.7.1 SIMULATED FLC COURSE-CHANGING

Course-changing was tested for two separate course-changes of 20° and 40°, each over a 50 second time period. These tests were repeated for the three vessel models, with comparison made to the conventional PID autopilot, regarding both heading and rudder data, in the manner discussed in section 7.4. For the course-changing tests no disturbance conditions were used so that the vessel responses obtained could be analysed without the presence of any spurious effects. The integral action was also inhibited on both the FLC and PID autopilots for the duration of these tests. Details of the test results are given in Tables 7.9 to 7.17.

	Course Change	PID	FLC	FLC/PID %
Rise Time (s)		28	3	-90
Overshoot (°)	20°	0	0	0
Settling Time (s)		43	16	-63
Rise Time (s)		28	5	-82
Overshoot (°)	40°	0	0	0
Settling Time (s)		40	22	-45

Table 7.9 Heading Results FLC and PID Course-Changing for 7.5m Model

	PID	FLC	FLC/PID %
RMS Rudder (°)	1.6	1.4	-12
Maximum Movement (°)	22	22	0
Range of Activity (°)	28	22	-12

Table 7.10 Rudder Results FLC and PID 20° Course-Change for the 7.5m Model

	PID	FLC	FLC/PID %
RMS Rudder (°)	3.2	3.2	0
Maximum Movement (°)	24	27	+12
Range of Activity (°)	25	27	+12

Table 7.11 Rudder Results FLC and PID 40° Course-Change for the 7.5m Model

	Course Change	PID	FLC	FLC/PID %
Rise Time (s)		16	3	-81
Overshoot (°)	20°	0	2	-
Settling Time (s)		23	25	+8
Rise Time (s)		17	6	-65
Overshoot (°)	40°	0	2	-
Settling Time (s)		24	14	-42

Table 7.12 Heading Results FLC and PID Course-Changing for 11.17m Model

	PID	FLC	FLC/PID %
RMS Rudder (°)	0.99	0.64	-15
Maximum Movement (°)	23	23	0
Range of Activity (°)	30	28	-7

Table 7.13 Rudder Results FLC and PID 20° Course-Change for the 11.17m Model

	PID	FLC	FLC/PID %
RMS Rudder (°)	1.8	1.3	-28
Maximum Movement (°)	26	28	+8
Range of Activity (°)	30	38	+27

Table 7.14 Rudder Results FLC and PID 40° Course-Change for the 11.17m Model

	Course Change	PID	FLC	FLC/PID %
Rise Time (s)		6	3	-50
Overshoot (°)	20	0	5	-
Settling Time (s)		16	14	-12
Rise Time (s)		12	5	-60
Overshoot (°)	40°	0	5	-
Settling Time (s)		22	21	-4

Table 7.15 Heading Results FLC and PID Course-Changing for 15m Model

	PID	FLC	FLC/PID %
RMS Rudder (°)	1.8	1.3	-28
Maximum Movement (°)	23	24	+4
Range of Activity (°)	41	43	+5

Table 7.16 Rudder Results FLC and PID 20° Course-Change for the 15m Model

	PID	FLC	FLC/PID %
RMS Rudder (°)	2.4	1.9	-19
Maximum Movement (°)	26	27	+4
Range of Activity (°)	45	52	+16

Table 7.17 Rudder Results FLC and PID 40° Course-Change for the 15m Model

7.7.2 SIMULATED FLC COURSE-KEEPING

After allowing sufficient time for the decay of any transient elements of the vessel's response, course-keeping was tested for a heading of 20° over a 120 second time period. These tests were repeated for the three vessel models, with comparison made to the conventional PID autopilot, regarding both heading and rudder data, in the manner discussed in section 7.5. All models were tested in the disturbance conditions associated with sea state 4, however, the 11.17m model was also tested in the sea state 3. Details of the test results are given in Tables 7.18 to 7.25.

	PID	FLC	FLC/PID %
Maximum Error (°)	25.7	25.3	N/A
Minimum Error (°)	18.0	17.6	N/A
Range of Error (°)	7.7	7.7	0
Variance	2.2	2.0	-9
Standard Deviation	1.5	1.3	-13

N/A = Not Applicable

Table 7.18 Heading Results FLC and PID Course-Keeping for the 7.5m Model in Sea Sate 4

	PID	FLC	FLC/PID %
Maximum Movement (°)	0.3	-0.2	N/A
Minimum Movement (°)	-11.2	-9.3	N/A
Range of Activity (°)	11.5	9.1	-21
Variance	2.6	2.2	-15
Standard Deviation	1.6	1.1	-31

N/A = Not Applicable

Table 7.19 Rudder Results FLC and PID Course-Keeping for the 7.5 m Model in Sea State 4

	PID	FLC	FLC/PID %
Maximum Error (°)	21.5	20.9	N/A
Minimum Error (°)	19.5	19.3	N/A
Range of Error (°)	2.0	1.6	-20
Variance	0.2	0.2	0
Standard Deviation	0.4	0.3	-25

N/A = Not Applicable

Table 7.20 Heading Results FLC and PID Course-Keeping for the 11.17m Model in Sea Sate 3

	PID	FLC	FLC/PID %
Maximum Movement (°)	-1.0	-1.0	N/A
Minimum Movement (°)	-2.3	-2.3	N/A
Range of Activity (°)	1.3	1.3	0
Variance	0.1	0.1	0
Standard Deviation	0.4	0.3	-25

N/A = Not Applicable

Table 7.21 Rudder Results FLC and PID Course-Keeping for the 11.17 m Model in Sea State 3

	PID	FLC	FLC/PID %
Maximum Error (°)	26.4	24.6	N/A
Minimum Error (°)	18.3	17.5	N/A
Range of Error (°)	8.1	7.1	-12
Variance	2.3	2.1	-9
Standard Deviation	1.5	1.4	-7

N/A = Not Applicable

Table 7.22 Heading Results FLC and PID Course-Keeping for the 11.17m Model in Sea Sate 4

	PID	FLC	FLC/PID %
Maximum Movement (°)	-0.7	-0.7	N/A
Minimum Movement (°)	-10.5	-9.3	N/A
Range of Activity (°)	9.8	8.6	-12
Variance	2.3	2.3	0
Standard Deviation	1.5	1.3	-13

N/A = Not Applicable

Table 7.23 Rudder Results FLC and PID Course-Keeping for the 11.17 m Model in Sea State 4

	PID	FLC	FLC/PID %
Maximum Error (°)	26.0	25.8	N/A
Minimum Error (°)	17.9	16.9	N/A
Range of Error (°)	8.1	8.9	+10
Variance	3.1	2.9	-6
Standard Deviation	1.8	1.7	-5

N/A = Not Applicable

Table 7.24 Heading Results FLC and PID Course-Keeping for the 15m Model in Sea Sate 4

	PID	FLC	FLC/PID %
Maximum Movement (°)	-0.3	-0.2	N/A
Minimum Movement (°)	-10.8	-10.9	N/A
Range of Activity (°)	10.5	10.7	+2
Variance	4.2	3.5	-17
Standard Deviation	2.1	1.8	-14

N/A = Not Applicable

Table 7.25 Rudder Results FLC and PID Course-Keeping for the 15m Model in Sea State 4

7.7.3 SIMULATED SOC COURSE-KEEPING

After allowing sufficient time for the decay of any transient elements of the vessel's response, course-keeping was tested for a heading of 20° over a 120 second time period. The learning was activated at the beginning of this test period utilising the time constant values given in section 7.7. These tests were repeated for the three vessel models, with comparison made to the conventional PID autopilot, regarding both heading and rudder data, in the manner discussed in section 7.6. All models were tested in the disturbance conditions associated with sea state 4, however, the 11.17m model was also tested in the sea state 3. Details of the test results are given in Tables 7.26 to 7.33.

	SOC	SOC/FLC %	SOC/PID %
Maximum Error (°)	25.4	N/A	N/A
Minimum Error (°)	17.4	N/A	N/A
Range of Error (°)	8	+4	+4
Variance	1.8	-10	-18
Standard Deviation	1.2	-8	-20

N/A = Not Applicable

Table 7.26 Heading Results SOC (Learning On) Course-Keeping for the 7.5m Model in Sea State 4

	SOC	SOC/FLC %	SOC/PID %
Maximum Movement (°)	-0.2	N/A	N/A
Minimum Movement (°)	-9.6	N/A	N/A
Range of Activity (°)	9.4	+3	-18
Variance	2.0	-9	-23
Standard Deviation	1.1	0	-31

N/A = Not Applicable

Table 7.27 Rudder Results SOC (Learning On) Course-Keeping for the 7.5m Model in Sea State 4

	SOC	SOC/FLC %	SOC/PID %
Maximum Error (°)	20.9	N/A	N/A
Minimum Error (°)	19.3	N/A	N/A
Range of Error (°)	1.6	0	-20
Variance	0.18	-10	-10
Standard Deviation	0.3	0	-25

N/A = Not Applicable

Table 7.28 Heading Results SOC (Learning On) Course-Keeping for the 11.17m Model in Sea State 3

	SOC	SOC/FLC %	SOC/PID %
Maximum Movement (°)	-1.0	N/A	N/A
Minimum Movement (°)	-2.3	N/A	N/A
Range of Activity (°)	1.3	0	0
Variance	0.1	0	0
Standard Deviation	0.28	-7	-30

N/A = Not Applicable

Table 7.29 Rudder Results SOC (Learning On) Course-Keeping for the 11.17m Model in Sea State 3

	SOC	SOC/FLC %	SOC/PID %
Maximum Error (°)	24.8	N/A	N/A
Minimum Error (°)	17.3	N/A	N/A
Range of Error (°)	7.5	+6	-7
Variance	1.8	-14	-22
Standard Deviation	1.2	-14	-20

N/A = Not Applicable

Table 7.30 Heading Results SOC (Learning On) Course-Keeping for the 11.17m Model in Sea State 4

	SOC	SOC/FLC %	SOC/PID %
Maximum Movement (°)	-0.7	N/A	N/A
Minimum Movement (°)	-9.5	N/A	N/A
Range of Activity (°)	8.8	+2	-10
Variance	2.1	-9	-9
Standard Deviation	1.2	-8	-20

N/A = Not Applicable

Table 7.31 Rudder Results SOC (Learning On) Course-Keeping for the 11.17m Model in Sea State 4

	SOC	SOC/FLC %	SOC/PID %
Maximum Error (°)	26.0	N/A	N/A
Minimum Error (°)	16.9	N/A	N/A
Range of Error (°)	9.1	+2	+12
Variance	2.7	-6	-13
Standard Deviation	1.6	-6	-11

N/A = Not Applicable

Table 7.32 Heading Results SOC (Learning On) Course-Keeping for the 15m Model in Sea State 4

	SOC	SOC/FLC %	SOC/PID %
Maximum Movement (°)	-0.2	N/A	N/A
Minimum Movement (°)	-10.1	N/A	N/A
Range of Activity (°)	9.9	-7	-6
Variance	3.1	-11	-26
Standard Deviation	1.8	0	-14

N/A = Not Applicable

Table 7.33 Rudder Results SOC (Learning On) Course-Keeping for the 15m Model in Sea State 4

7.7.4 DISCUSSION OF SIMULATED RESULTS

In general the simulated test results confirm the findings of the sea trial results. When considering course-changing, the rise times were all significantly faster when compared to the conventional PID autopilot due to the non-linear FLC design. For small magnitude heading errors a similar response was obtained and therefore settling times were correspondingly improved. Overshoots occurred which appear to increase with the change in vessel length, however, their magnitude remains small and they therefore remain acceptable. This significant improvement in course-changing performance is achieved whilst employing a reduced RMS rudder value and thus lower power usage and drag effects.

For course-keeping the FLC has been demonstrated to achieve an increase in performance on all models tested. The heading error performance was improved, whilst both the variance and standard deviation of the rudder activity were reduced. By employing the SOC learning, these values were improved still further. The level of improvement generated during learning was not as significant as that found during the sea trials, however, the learning time was considerably less. Given that the learning was designed to be a gradual process, this result is as expected.

7.8 CONCLUSIONS

In this Chapter, the validation of three aspects of the new SOC autopilot via full scale sea trials, and by simulation, has been presented:

1. FLC course-changing
2. FLC course-keeping
3. SOC learning during course-keeping

Whilst the simulated results are required to demonstrate the general applicability of the new autopilot design, it is the sea trial results which are of most importance when analysing any performance advantage because they represent actual conditions in a real working environment.

The FLC is an integral part of the SOC and therefore reference to FLC course-changing and course-keeping is a consideration of the SOC with learning inhibited. As discussed in Chapter 6, the learning will always remain inhibited during the course-changing mode of operation.

During course-changing the performance advantage obtained, during the sea trials, by the FLC for the 90° was considerable, when compared to the PID, with a 50% reduction in rise time. However, due to the non-linear FLC designed, the autopilot operated in a more sensitive manner for smaller heading errors. The values contained within the enhancement matrix represent lower rudder ratio values for small errors and increased counter rudder values. Because of this design feature, overshoot of the desired heading was avoided despite the fast rate of turn. As expected, for the smaller magnitude course changes, the PID and FLC results were more similar. Even so, the 2° overshoot of the PID was reduced to zero by the FLC. The operation of the FLC, when course-changing, may be considered as significant, given that both controllers were initiated with identical gain values.

In course-keeping mode, the FLC again out-performed the PID controller in all fields of analysis. The FLC maintained a significantly closer course (50% improvement) with a much smoother and consistent vessel motion. To achieve this advantage, the range of rudder movement was reduced by 49%. Analysis of the rudder response identifies that the majority of the rudder actions were in the form of comparatively small, but controlled, movements compared to the wandering rudder of the PID. The FLC's improved course-keeping ability, for the same gain settings, was therefore established.

However, when undertaking the same test with the SOC, it was found that the learning further improved upon the FLC's performance by observing the performance of the vessel, and subsequently modifying the enhancement matrices. By deciding to selectively employ small increases in rudder, the SOC managed to reduce the range of heading error variance by a further 45% giving a total reduction of 75%. Whilst the range of rudder movement consequently was increased, the rudder's variance was also reduced by 27% of the FLC's value.

The performance ability of the three main aspects of the SOC have therefore been discussed when operating in typical conditions and a characteristic size of vessel. However, no aspect of the SOC was designed specifically for this test vessel. The rudder ratio, counter rudder and trim settings are all variable. Since the enhancements matrices were designed non-dimensionally, their operation is relative to the rudder ratio and counter rudder settings. Any non-linear advantage demonstrated in these tests should therefore be transferable to other gain settings, and hence to other vessels and conditions. However, the non-linear nature of the controller is likely to increase the robustness of the FLC design when gain settings diverge from their optimal values.

7.9 REFERENCES

7.1 Nomoto K., Taguchi T., Honda K., and Hirano S. "On the Steering Qualities of Ships." Proc. Int. Shipbuilding Progress, Vol. 4, No. 35, pp 354-370, 1957.

7.2 Burns R.S., Dove M.J. and Miller K.M. "A Control and Guidance System for Ships in Port Approaches." Proc. IMarE Conference on Communications and Control, London, October, 1988.

CHAPTER 8. CONCLUSIONS AND RECOMMENDATIONS

The conventional PID autopilot is widely used for ship control across the world. It is considered to be reliable, simple to operate and effective, which are all realistic interpretations of its performance capabilities when applied to large ships. In practice, the PID's reliability is due as much to the quality of the hardware and software used to implement it, as to the nature of the algorithm itself.

The need for a new design of small vessel autopilot which is capable of non-linear performance, and of adapting itself to obtain high performance levels, even when the gain settings are incorrect, was established in section 1.2. This new autopilot would be independent of the mariner's experience and could operate on the wide range of vessel type which currently defines the market for this type of controller. By employing a new method of control, the autopilot's abilities in both the modes of course-changing and course-keeping could also be improved, thus providing a very significant increase in autopilot performance when compared to the PID alternative.

From the literature cited in section 2.4, it is clear that there has been only limited work on new ship autopilot designs. Of the modern control techniques utilised in this field, all have been applied to the case of large ships and there is no comparable work for the small vessel application.

Both neural networks (Chapter 3) and fuzzy logic (Chapter 4) were considered for use in the new autopilot design. Neural networks require a large amount of training data prior to implementation in order that supervised learning may take place. In addition, the size of the network necessary to achieve non-linear control required the storage, and eventual on-line adaption, of a significant number of weight values. The time requirement for such an operation was considered impractical for the large network required to cope with the necessary non-linearities and also the autopilot's fast sampling of 0.88 ms. Conversely, fuzzy logic could utilise a limited amount of data derived from the PID algorithm. Non-linear design was possible without imposing excessive problems with data storage, and subsequent extension to an adaptive form, the SOC, remained realistic within the sample period dictated by the autopilot hardware, as described in Appendix A.

Work on the new design of fuzzy logic autopilot was therefore undertaken (Chapter 5) for the two modes of autopilot operation, these being course-keeping and course-changing. The new design, section 5.2, utilised non-linear input windows to allow for the combination of course-keeping and course-changing within one controller. To prevent the resultant controller from becoming computationally oversized, relatively few points were defined, with interpolation between them to maintain input resolution. Similarly, the rulebase was defined, section 5.4, in a non-linear manner, thus generating an increase in performance levels from the controller.

One major problem with the commercial PID autopilot is that its gain values are fixed for large and small heading errors, and for both course-changing and course-keeping modes of operation. By creating this non-linear rulebase, the rudder ratio gain could be increased, and the counter rudder gain decreased for large heading errors and during the majority of the course-changing mode, whilst smaller rudder ratio gains and larger counter rudder gains could be employed for small heading errors and for the final stages of course-changing when a more precise level of control is required.

The third input, called trim, was then included by shifting the deterministic fuzzy output to positive, or negative, within the fuzzy output window, as described in section 5.3. To achieve a suitable resolution of movement for the trim term within this window, the window itself was defined by two hundred and one fuzzy singletons instead of the conventional seven set approach.

This initial design of fuzzy controller had fixed rulebase values which could not be adjusted to operate at different gain settings either by adaption, or by the mariner. The single rulebase, representing both rudder ratio and counter rudder, was therefore replaced by two enhancement matrices, one for rudder ratio and the other for counter rudder, as described in section 6.4. Each enhancement matrix was of the identical structure to the original rulebase, but instead of containing output set information, the data within them represented how the respective rudder ratio and counter rudder gains should be modified (enhanced) depending upon which combination of fuzzy sets were identified when the real world inputs of head error and rate of change of heading error were fuzzified, e.g. for large heading errors the rudder ratio gain could be significantly enhanced, thus generating a large effective rudder ratio value, whereas for small heading errors the rudder ratio could remain unchanged.

By defining each enhancement matrix in terms of a proportional change dependant upon the rudder ratio and counter rudder gain settings, the fuzzy controller design became non-dimensional and could therefore operate, with pro-rata performance advantages, over a range of rudder ratio and counter rudder settings. In addition, the use of the enhancement matrices allowed identification of the individual rudder ratio and counter rudder gain terms over the defined operating envelope. By employing a performance index for each enhancement matrix (section 6.5), learning could be achieved in an on-line manner, to adjust the relative elements of each enhancement matrix until an acceptable level of performance was achieved by the autopilot. The learning was carried out in a two stage approach:

1. Data was stored which represented the elements of the enhancement matrices used at the current sample time, section 6.7.1.

2. At a time period later, which represented approximately three time constants of the overall vessel response, adjustment to those enhancement matrix elements

was carried out. The magnitude of the adjustment was determined by applying the new vessel performance, in terms of heading error and rate of change of heading error, to the performance index. The aggregate output from the performance index was then scaled and utilised to modify the enhancement matrix elements identified previously as being responsible for the current performance state, section 6.7.2.

The SOC learning was carried out in parallel to the trim adaption, which identified the presence of an uncorrected steady-state error and increased the trim gain accordingly, section 6.8. Similarly, when no steady-state error was present, but the rate of change of heading error input was high, then the trim term was reduced until a point of equilibrium occurred. Both SOC learning and trim adaption were controlled by over-rules (section 6.7.3) which ensured that the learning achieved was correct and therefore enhanced autopilot performance.

Due to the requirements of this application, the final SOC has been shown to differ greatly from any previous marine designs. Whilst the use of non-linearities is not new, the style of input windows and rulebase, designed and developed during this research, are specific to this application and have demonstrated major performance advantages in comparison to the conventional PID autopilot. The subsequent use of the enhancement matrix is a unique advancement in autopilot design and has been seen to further increase the performance potential of this new autopilot design.

The additional implementation of the trim term, using the fuzzy singleton output window, whilst certainly unorthodox, has proved of significant benefit to the ability of the controller when operating in the required range of environmental conditions. When considering the SOC's learning, the design of the performance indices was application dependant and the manner in which the learning was achieved is new, simple and proven to be effective by the validation tests in Chapter 7 .

When utilised in both sea trials and simulation, and operating with the same gain settings, all aspects of the SOC were found to give a significant increase in performance compared to the PID autopilot. The ability of the SOC to operate as a small vessel autopilot has therefore been established. However, before any commercial implementation is possible it is necessary that further sea tests are carried out in order to produce a record of successful installations on differing vessel types, and thus to ensure that safety at sea is maintained. Despite the inevitable delay that will occur due to this testing, it is envisaged that the new SOC autopilot for use on small vessels should be available in the commercial market place in the near future.

The structure of the final SOC design contains many features which have been incorporated specifically for this application, however, most of the routines may be considered to be design independent. The inference may therefore be drawn that performance advantages obtained in comparison to this PID autopilot, may also be possible in other applications where PID controllers are currently in use.

The scope for the development of this SOC design is therefore significant and should be considered as a further extension of this work. It is also noted by the author that since undertaking this study, there has been considerable work published in the field of neuro-fuzzy control. This type of controller is an attempt to merge the benefits of both fuzzy logic and neural networks into a single control algorithm and could prove of benefit to the small vessel application in the future.

The present work may be considered as part of an overall ship automation process. Gradually many human tasks on all sizes of marine vessel are becoming automated on an individual basis. However, in the case of large shipping it is thought that the ultimate goal may be a fully automated, and therefore unmanned ship.

For the small vessel application such a goal is perhaps less realistic given that use in congested ports and sea-ways is far more common. Should the level of technology become advanced enough to cope with such complexities, then it may be possible in the future to link the various automated systems currently available to produce a full level of ship automation which includes collision avoidance, track-keeping, navigation and autopilot control.

If the purpose of many small vessels is for human pleasure, gained from being at sea, not from the activities which are demanded from the mariner, then perhaps the increased safety and time afforded by a perfect automated system would allow more less experienced humans, e.g. people on holiday or with disabilities, to enjoy an otherwise closed opportunity. The likelihood of any system being perfect is currently remote, but future work dedicated in this area, could certainly reduce the risk involved to an acceptable, and therefore implementable level. By this means, the possible use of small vessels could be expanded significantly with consequential commercial implications throughout the industry.

APPENDIX A - FURTHER DETAILS OF THE CONVENTIONAL PID TEST AUTOPILOT

A.1 INTRODUCTION

Many of the PID autopilot's particulars are specific to the collaborating manufacturer's products. It can not be inferred from this work that identical features may be found on all competitive products, however, it is a natural assumption, that within the small vessel "market place", the alternative autopilots will have been designed along broadly similar lines.

A.2 AUTOPILOT OPERATIONAL CONSIDERATIONS

Since typical movement of the rudder mechanism is within the range ±20° to ±30°, a variable term is provided called Max Rudder Angle (MRA) which can be adjusted from 1 to 9 to match the vessel's requirements (Table A.1).

Rudder Limit Setting	Physical Rudder Limit
1	6°
2	9°
3	12°
4	15°
5	18°
6	21°
7	24°
8	27°
9	30°

TABLE A.1 DEFINITION OF RUDDER LIMIT SETTINGS

The rudder limit imposed by the controller is determined by equation A.1.

$$\text{Limit} = (\text{MRA} + 1) * 3 \tag{A.1}$$

As variations in the weather occur, then a rudder deadband (RDB) facility can be employed to inhibit small scale rudder movements which are deemed as being unnecessary. Further rudder "hunting" can also occur in rudder systems where "slack" has been caused by wear, and thus small uncontrolled rudder movement may continue regardless of the autopilot operation. The rudder deadband can be adjusted in the range 0 to 9, as defined in Table A.2, to lessen these effects.

Rudder Deadband Setting	Actual Rudder Deadband
0	0.0°
1	0.2°
2	0.4°
3	0.6°
4	0.8°
5	1.1°
6	1.3°
7	1.5°
8	1.7°
9	2.0°

TABLE A.2 DEFINITION OF RUDDER DEADBAND SETTINGS

In addition, a weather setting to initiate a course deadband (CDB) may be employed to avoid excessive rudder activity as seas become heavier. The course deadband is a zone in which no new control action is produced, and can be defined in the range 0 to 9 (Table A.3).

Whilst within the CDB zone the desired rudder remains constant so that the rudder system is provided with an opportunity to reach this desired position, where it will remain until the vessel heading error leaves the deadband. At this point a new corrective action is determined to ensure that the heading error returns to within the defined zone.

Course Deadband Settings	Actual Course Deadband
0	0.0°
1	1.0°
2	2.0°
3	3.0°
4	4.0°
5	5.0°
6	6.0°
7	7.0°
8	8.0°
9	9.0°

TABLE A.3 DEFINITIONS OF COURSE DEADBAND SETTINGS

Heavy seas can greatly effect the vessel heading, thus in this situation the rudder effort to maintain a tight course becomes considerable. Performance in such conditions must be expected to be less than that achieved in calm seas, therefore the introduction of the course deadband allows the reduction in the rudder activity without reducing the rudder ratio value which would have a detrimental effect across the entire operating range.

The component parts of the PID controller utilised in the conventional autopilot can be identified separately and are defined by equations A.2 to A.4.

$$\text{Proportional Term} = \frac{(\text{RR}+1) * \text{Error}}{10} \qquad \text{(A.2)}$$

$$\text{Integral Term} = \frac{\sum_{0}^{n}(5.3 * \text{TRIM} * \text{Error})}{65536} \qquad \text{(A.3)}$$

$$\text{Derivative Term} = CR * \text{Rate} \tag{A.3}$$

where:

RR = Proportional gain (rudder ratio setting)

TRIM = Integral gain (Trim setting)

CR = Derivative gain (counter rudder setting)

Error = Heading error

Rate = Rate of change of heading error

n = number of samples included in summation

When the heading error falls within the course deadband, then no increments, or decrements, to the integral action occur. In addition, when a course-changing manoeuvre commences, any adjustment of the integral term is delayed by 10 seconds. Saturation excursion limits of two thirds rudder movement are applied to both the derivative and integral terms to prevent the magnitude of either term from becoming excessive. The three terms are then summed together to generate a value for the desired rudder signal, which is the output from the PID autopilot (equation A.4).

$$\text{Desired Rudder} = [\text{Proportion Term} + \text{Integral Term} + \text{Derivative Term}] \tag{A.4}$$

Typical settings for the autopilot variables of most interest to this study are given in Table A.4.

Even though the desired rudder has been calculated, the actual rudder system's time constant will cause a delay before the correct position can be obtained. Further to this, the time constant of the vessel will effect the speed with which any corrective action will be acted upon. New values of desired rudder are calculated by the PID controller every sample. The sample time is set to 88 ms which equates to 11.36 samples every second.

Variable Name	Variable Setting
RR	6
TRIM	4
CR	3
RDB	1
MRA	8

TABLE A.4 TYPICAL AUTOPILOT SETTINGS

It is also possible, within the autopilot environment, to set pre-defined gain values for variations in forward velocity, e.g. high and low (assuming a forward velocity sensor is fitted), and also for boat type, e.g. displacement, semi-displacement and planning. Whilst the forward velocity option works automatically, the boat type setting is reliant upon manual change. In both cases the gain settings stored are those chosen by the mariner. There are additional autopilot settings available which have not been described as they hold no direct relevance to the study described herein.

The integral term, desired rudder value, and any other calculated terms are cleared when the autopilot is taken out of pilot mode (autopilot control) and placed in standby mode (manual control). Default values are therefore utilised whenever the pilot mode is activated, however alterations in gain settings and deadband values are stored in the permanent memory and will be recalled even after a power shut down has occurred.

The complete autopilot system requires an operational supply voltage between 9.6 Volts and 32.0 Volts DC and comprises a series of component parts. Each part is linked by a data bus. The format for the bus is the marine industry standard specified by the National Marine Electronics Association of North America (NMEA 0183).

Whilst each unit operates independently on its allocated tasks, they must all combine together correctly if effective autopilot control is to be achieved. The basic system, the standard layout of which is shown in Figure A.1, therefore contains six fundamental operating units, these are:

1. Pilot Control Unit
2. Compass Controller Unit
3. Motor Drive Unit
4. Rudder Feedback Unit
5. Power Steering System (Including Rudder)
6. Mobile Hand Control Unit (Optional)

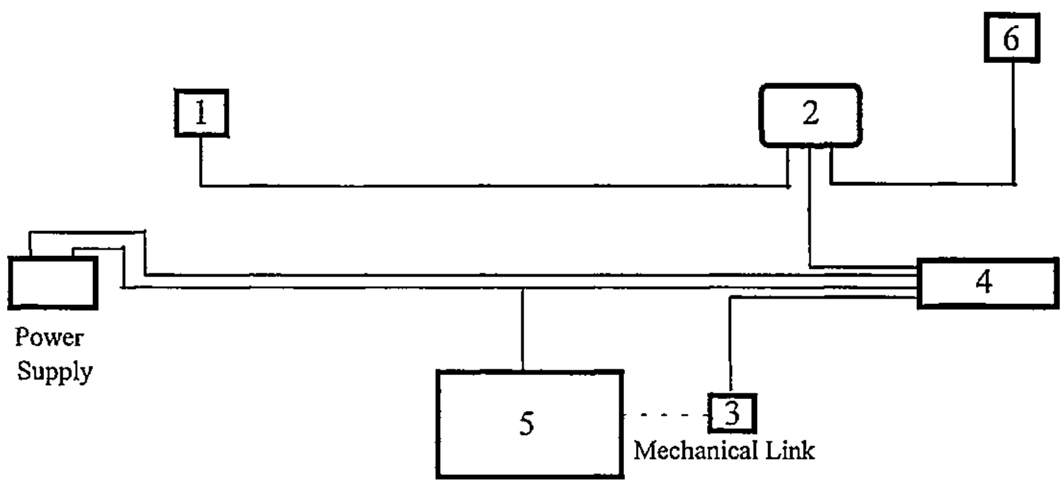

FIGURE A.1 STANDARD AUTOPILOT SYSTEM LAYOUT

The compass controller receives and processes all the data from the sensory devices fitted to the system. The compass controller also contains the fluxgate compass which generates fast high precision heading information. Adaptive damping of the compass data ensures steady heading information even when operating in heavy seas. Also included are the electronic circuitry, microprocessor and software required for autopilot operation. Features included pulse width modulation (PWM) speed control for the steering motor. The solid state Field Effect Transistor (FET)

unit employs soft switching to minimise radio frequency interference (RFI) often associated with this type of semiconductor. Human interface is achieved via the pilot control unit which allows adjustment of the various settings, and in turn displays information concerning actual heading and desired course.

The steering system attempts to position the rudder correctly following the motor signal provided by the FET unit. Actual rudder positional information is produced by the rudder feedback device. This data is returned to the compass controller where an analysis of the rudder position undertaken by the software, and a comparison between the desired position and actual position generates a rudder positional error. A more detailed description concerning the C-net pilot is given in the user's manual [A.1].

The actual autopilot software comprises of a series of modules written in 'C' code and compiled and linked together for operation on a 16 bit HPC micro-processor unit (MPC). The MPC is capable of high speed data processing and utilises a 16 MHz clock frequency. The compiled code is activated from an Erasable Programmable Read Only Memory (EPROM) situated within the compass control unit. Space on the EPROM is obviously limited, with almost total occupation by the existing conventional software. In order that available memory could be conserved, the use of floating point type numbers (4 bytes) was avoided, as was the use of floating point arithmetic. Integer type values (2 bytes) were also considered excessive in size. Therefore the majority of the control routines attempt to utilise char types (1 byte) whenever possible. The relevant overall memory limits for Read Only Memory (ROM) and Random Access Memory (RAM), including 8 bit and 16 bit capabilities, in hexadecimal format are specified in table A.5.

Type of Memory	Memory Size (bytes)
BASE	0
RAM16	01D4
RAM8	01FF
ROM16	0
ROM8	7F0F

TABLE A.5 EPROM MEMORY LIMITATIONS

A.3 REFERENCES

A.1 C-net Pilot User's Guide, Cetrek Ltd, Ref. 807-600-9-93, 1993.

APPENDIX B - VALIDATION OF THE FOUNDATION FLC METHODOLOGY

B.1 INTRODUCTION

The following results are for the FLC described in section 5.4. using inputs of heading error and rate of change of heading error in the ranges ±15° and ±2°s^{-1} respectively. By varying these two input values within their given ranges of operation, in steps of 0.5° for heading error and 0.1°s^{-1} for rate of change of heading error, the outputs from the FLC and PID autopilots could be compared. Integral action was inhibited for both autopilots during testing, and the rulebase for the FLC was designed to mimic the expected from the PID autopilot.

Because the methodologies of both the FLC and PID are so radically different, it is unreasonable to expect an exact match between the two sets of results without extensive fine tuning of the fuzzy rulebase to allow for the uneven overlap of fuzzy sets caused by the non-linear fuzzy put window design being utilised.

B.2 CONSIDERATION OF THE TEST RESULTS

After consideration of the test results which follow, three conclusions are possible:

1. The controller operates in a symmetrical manner about the zero input condition for both inputs considered. The FLC is therefore capable of providing equal control to both port and starboard.

2. The output from the FLC autopilot closely follows that of the conventional PID autopilot, the difference never exceeding ±0.5° from a range of ±30°. Given the nature of the test, this result is considered perfectly acceptable.

3. For the given level of performance obtained from the FLC, the resolutions used within the FLC autopilot must be adequate, there being no significant loss of performance when compared to the PID alternative.

It may therefore be concluded that if the FLC is capable of operating in the same manner to the conventional PID autopilot, then any subsequent redesigning of the rulebase to a non-linear format, may be undertaken with a high degree of confidence in the FLC's capabilities as a small vessel autopilot.

Rate (°/s)	Error (°)	FLC (°)	PID (°)	Diff (°)
-2	-15	-16.5	-16.5	0
-2	-14.5	-16.2	-16.15	0.05
-2	-14	-15.8	-15.8	0
-2	-13.5	-15.45	-15.45	0
-2	-13	-15.15	-15.1	0.05
-2	-12.5	-14.75	-14.75	0
-2	-12	-14.4	-14.4	0
-2	-11.5	-14.05	-14.05	0
-2	-11	-13.7	-13.7	0
-2	-10.5	-13.35	-13.35	0
-2	-10	-13	-13	0
-2	-9.5	-12.65	-12.65	0
-2	-9	-12.3	-12.3	0
-2	-8.5	-12	-11.95	0.05
-2	-8	-11.65	-11.6	0.05
-2	-7.5	-11.3	-11.25	0.05
-2	-7	-10.95	-10.9	0.05
-2	-6.5	-10.65	-10.55	0.1
-2	-6	-10.3	-10.2	0.1
-2	-5.5	-9.95	-9.85	0.1
-2	-5	-9.65	-9.5	0.15
-2	-4.5	-9.3	-9.15	0.15
-2	-4	-8.95	-8.8	0.15
-2	-3.5	-8.6	-8.45	0.15
-2	-3	-8.25	-8.1	0.15
-2	-2.5	-7.9	-7.75	0.15
-2	-2	-7.55	-7.4	0.15
-2	-1.5	-7.2	-7.05	0.15
-2	-1	-6.8	-6.7	0.1
-2	-0.5	-6.45	-6.35	0.1
-2	0	-6.15	-6	0.15
-2	0.5	-5.8	-5.65	0.15
-2	1	-5.45	-5.3	0.15
-2	1.5	-5.1	-4.95	0.15
-2	2	-4.7	-4.6	0.1
-2	2.5	-4.35	-4.25	0.1
-2	3	-4	-3.9	0.1
-2	3.5	-3.65	-3.55	0.1
-2	4	-3.3	-3.2	0.1
-2	4.5	-3	-2.85	0.15
-2	5	-2.6	-2.5	0.1
-2	5.5	-2.25	-2.15	0.1
-2	6	-1.85	-1.8	0.05
-2	6.5	-1.5	-1.45	0.05
-2	7	-1.15	-1.1	0.05
-2	7.5	-0.75	-0.75	0
-2	8	-0.35	-0.4	-0.05
-2	8.5	0	-0.05	-0.05
-2	9	0.3	0.3	0
-2	9.5	0.65	0.65	0
-2	10	1	1	0
-2	10.5	1.35	1.35	0

-2	11	1.7	1.7	0
-2	11.5	2.05	2.05	0
-2	12	2.4	2.4	0
-2	12.5	2.75	2.75	0
-2	13	3.15	3.1	0.05
-2	13.5	3.45	3.45	0
-2	14	3.8	3.8	0
-2	14.5	4.2	4.15	0.05
-2	15	4.5	4.5	0
-1.5	-15	-14.95	-15	-0.05
-1.5	-14.5	-14.5	-14.65	-0.15
-1.5	-14	-14	-14.3	-0.3
-1.5	-13.5	-13.7	-13.95	-0.25
-1.5	-13	-13.45	-13.6	-0.15
-1.5	-12.5	-13.2	-13.25	-0.05
-1.5	-12	-13	-12.9	0.1
-1.5	-11.5	-12.8	-12.55	0.25
-1.5	-11	-12.6	-12.2	0.4
-1.5	-10.5	-12.3	-11.85	0.45
-1.5	-10	-11.95	-11.5	0.45
-1.5	-9.5	-11.45	-11.15	0.3
-1.5	-9	-10.85	-10.8	0.05
-1.5	-8.5	-10.3	-10.45	-0.15
-1.5	-8	-9.95	-10.1	-0.15
-1.5	-7.5	-9.7	-9.75	-0.05
-1.5	-7	-9.5	-9.4	0.1
-1.5	-6.5	-9.3	-9.05	0.25
-1.5	-6	-9.1	-8.7	0.4
-1.5	-5.5	-8.8	-8.35	0.45
-1.5	-5	-8.4	-8	0.4
-1.5	-4.5	-7.75	-7.65	0.1
-1.5	-4	-7.35	-7.3	0.05
-1.5	-3.5	-7.05	-6.95	0.1
-1.5	-3	-6.85	-6.6	0.25
-1.5	-2.5	-6.65	-6.25	0.4
-1.5	-2	-6.3	-5.9	0.4
-1.5	-1.5	-5.65	-5.55	0.1
-1.5	-1	-5.2	-5.2	0
-1.5	-0.5	-4.95	-4.85	0.1
-1.5	0	-4.75	-4.5	0.25
-1.5	0.5	-4.55	-4.15	0.4
-1.5	1	-4.2	-3.8	0.4
-1.5	1.5	-3.55	-3.45	0.1
-1.5	2	-3.1	-3.1	0
-1.5	2.5	-2.85	-2.75	0.1
-1.5	3	-2.65	-2.4	0.25
-1.5	3.5	-2.45	-2.05	0.4
-1.5	4	-2.05	-1.7	0.35
-1.5	4.5	-1.45	-1.35	0.1
-1.5	5	-0.9	-1	-0.1
-1.5	5.5	-0.55	-0.65	-0.1
-1.5	6	-0.25	-0.3	-0.05
-1.5	6.5	-0.05	0.05	0

-1.5	7	0.1	0.4	-0.3
-1.5	7.5	0.35	0.75	-0.4
-1.5	8	0.7	1.1	-0.4
-1.5	8.5	1.15	1.45	-0.3
-1.5	9	1.85	1.8	0.05
-1.5	9.5	2.4	2.15	0.25
-1.5	10	2.8	2.5	0.3
-1.5	10.5	3.1	2.85	0.25
-1.5	11	3.35	3.2	0.15
-1.5	11.5	3.6	3.55	0.05
-1.5	12	3.8	3.9	-0.1
-1.5	12.5	3.95	4.25	-0.3
-1.5	13	4.2	4.6	-0.4
-1.5	13.5	4.5	4.95	-0.45
-1.5	14	4.9	5.3	-0.4
-1.5	14.5	5.4	5.65	-0.25
-1.5	15	6	6	0
-1	-15	-13.5	-13.5	0
-1	-14.5	-12.95	-13.15	-0.2
-1	-14	-12.4	-12.8	-0.4
-1	-13.5	-12	-12.45	-0.45
-1	-13	-11.7	-12.1	-0.4
-1	-12.5	-11.5	-11.75	-0.25
-1	-12	-11.3	-11.4	-0.1
-1	-11.5	-11.1	-11.05	0.05
-1	-11	-10.85	-10.7	0.15
-1	-10.5	-10.6	-10.35	0.25
-1	-10	-10.3	-10	0.3
-1	-9.5	-9.9	-9.65	0.25
-1	-9	-9.35	-9.3	0.05
-1	-8.5	-8.75	-8.95	-0.2
-1	-8	-8.3	-8.6	-0.3
-1	-7.5	-8	-8.25	-0.25
-1	-7	-7.75	-7.9	-0.15
-1	-6.5	-7.55	-7.55	0
-1	-6	-7.35	-7.2	0.15
-1	-5.5	-7.1	-6.85	0.25
-1	-5	-6.8	-6.5	0.3
-1	-4.5	-6.3	-6.15	0.15
-1	-4	-5.7	-5.8	-0.1
-1	-3.5	-5.3	-5.45	-0.15
-1	-3	-5.1	-5.1	0
-1	-2.5	-4.9	-4.75	0.15
-1	-2	-4.65	-4.4	0.25
-1	-1.5	-4.2	-4.05	0.15
-1	-1	-3.55	-3.7	-0.15
-1	-0.5	-3.2	-3.35	-0.15
-1	0	-3	-3	0
-1	0.5	-2.8	-2.65	0.15
-1	1	-2.55	-2.3	0.25
-1	1.5	-2.1	-1.95	0.15
-1	2	-1.45	-1.6	-0.15
-1	2.5	-1.05	-1.25	-0.2

-1	3	-0.85	-0.9	-0.05
-1	3.5	-0.65	-0.55	0.1
-1	4	-0.35	-0.2	0.15
-1	4.5	0.05	0.15	-0.1
-1	5	0.75	0.5	0.25
-1	5.5	1.15	0.85	0.3
-1	6	1.5	1.2	0.3
-1	6.5	1.7	1.55	0.15
-1	7	1.9	1.9	0
-1	7.5	2.15	2.25	-0.1
-1	8	2.45	2.6	-0.15
-1	8.5	2.8	2.95	-0.15
-1	9	3.35	3.3	0.05
-1	9.5	3.95	3.65	0.3
-1	10	4.45	4	0.45
-1	10.5	4.8	4.35	0.45
-1	11	5.1	4.7	0.4
-1	11.5	5.3	5.05	0.25
-1	12	5.5	5.4	0.1
-1	12.5	5.7	5.75	-0.05
-1	13	5.95	6.1	-0.15
-1	13.5	6.2	6.45	-0.25
-1	14	6.55	6.8	-0.25
-1	14.5	7	7.15	-0.15
-1	15	7.45	7.5	-0.05
-0.5	-15	-12	-12	0
-0.5	-14.5	-11.4	-11.65	-0.25
-0.5	-14	-10.9	-11.3	-0.4
-0.5	-13.5	-10.5	-10.95	-0.45
-0.5	-13	-10.3	-10.6	-0.3
-0.5	-12.5	-10.05	-10.25	-0.2
-0.5	-12	-9.8	-9.9	-0.1
-0.5	-11.5	-9.55	-9.55	0
-0.5	-11	-9.35	-9.2	0.15
-0.5	-10.5	-9.1	-8.85	0.25
-0.5	-10	-8.8	-8.5	0.3
-0.5	-9.5	-8.35	-8.15	0.2
-0.5	-9	-7.85	-7.8	0.05
-0.5	-8.5	-7.25	-7.45	-0.2
-0.5	-8	-6.8	-7.1	-0.3
-0.5	-7.5	-6.55	-6.75	-0.2
-0.5	-7	-6.3	-6.4	-0.1
-0.5	-6.5	-6.1	-6.05	0.05
-0.5	-6	-5.85	-5.7	0.15
-0.5	-5.5	-5.6	-5.35	0.25
-0.5	-5	-5.3	-5	0.3
-0.5	-4.5	-4.8	-4.65	0.15
-0.5	-4	-4.2	-4.3	-0.1
-0.5	-3.5	-3.85	-3.95	-0.1
-0.5	-3	-3.65	-3.6	0.05
-0.5	-2.5	-3.4	-3.25	0.15
-0.5	-2	-3.15	-2.9	0.25
-0.5	-1.5	-2.7	-2.55	0.15

-0.5	-1	-2.05	-2.2	-0.15
-0.5	-0.5	-1.7	-1.85	-0.15
-0.5	0	-1.5	-1.5	0
-0.5	0.5	-1.25	-1.15	0.1
-0.5	1	-1	-0.8	0.2
-0.5	1.5	-0.5	-0.45	0.05
-0.5	2	0.1	-0.1	0
-0.5	2.5	0.45	0.25	0.2
-0.5	3	0.75	0.6	0.15
-0.5	3.5	1	0.95	0.05
-0.5	4	1.3	1.3	0
-0.5	4.5	1.8	1.65	0.15
-0.5	5	2.4	2	0.4
-0.5	5.5	2.8	2.35	0.45
-0.5	6	3.05	2.7	0.35
-0.5	6.5	3.3	3.05	0.25
-0.5	7	3.5	3.4	0.1
-0.5	7.5	3.75	3.75	0
-0.5	8	4	4.1	-0.1
-0.5	8.5	4.35	4.45	-0.1
-0.5	9	4.85	4.8	0.05
-0.5	9.5	5.45	5.15	0.3
-0.5	10	5.95	5.5	0.45
-0.5	10.5	6.3	5.85	0.45
-0.5	11	6.55	6.2	0.35
-0.5	11.5	6.75	6.55	0.2
-0.5	12	7	6.9	0.1
-0.5	12.5	7.25	7.25	0
-0.5	13	7.5	7.6	-0.1
-0.5	13.5	7.7	7.95	-0.25
-0.5	14	8.05	8.3	-0.25
-0.5	14.5	8.5	8.65	-0.15
-0.5	15	9	9	0
0	-15	-10.5	-10.5	0
0	-14.5	-9.95	-10.15	-0.2
0	-14	-9.45	-9.8	-0.35
0	-13.5	-9.1	-9.45	-0.35
0	-13	-8.85	-9.1	-0.25
0	-12.5	-8.6	-8.75	-0.15
0	-12	-8.4	-8.4	0
0	-11.5	-8.2	-8.05	0.15
0	-11	-8	-7.7	0.3
0	-10.5	-7.7	-7.35	0.35
0	-10	-7.4	-7	0.4
0	-9.5	-6.9	-6.65	0.25
0	-9	-6.35	-6.3	0.05
0	-8.5	-5.8	-5.95	-0.15
0	-8	-5.4	-5.6	-0.2
0	-7.5	-5.1	-5.25	-0.15
0	-7	-4.85	-4.9	-0.05
0	-6.5	-4.7	-4.55	0.15
0	-6	-4.5	-4.2	0.3
0	-5.5	-4.2	-3.85	0.35

0	-5	-3.85	-3.5	0.35
0	-4.5	-3.3	-3.15	0.15
0	-4	-2.75	-2.8	-0.05
0	-3.5	-2.45	-2.45	0
0	-3	-2.25	-2.1	0.15
0	-2.5	-2.05	-1.75	0.3
0	-2	-1.7	-1.4	0.3
0	-1.5	-1.2	-1.05	0.15
0	-1	-0.55	-0.7	-0.15
0	-0.5	-0.2	-0.35	-0.15
0	0	0	0	0
0	0.5	0.2	0.35	-0.15
0	1	0.55	0.7	-0.15
0	1.5	1.2	1.05	0.15
0	2	1.7	1.4	0.3
0	2.5	2.05	1.75	0.3
0	3	2.25	2.1	0.15
0	3.5	2.45	2.45	0
0	4	2.75	2.8	-0.05
0	4.5	3.3	3.15	0.15
0	5	3.85	3.5	0.35
0	5.5	4.2	3.85	0.35
0	6	4.5	4.2	0.3
0	6.5	4.7	4.55	0.15
0	7	4.85	4.9	-0.05
0	7.5	5.1	5.25	-0.15
0	8	5.4	5.6	-0.2
0	8.5	5.8	5.95	-0.15
0	9	6.35	6.3	0.05
0	9.5	6.9	6.65	0.25
0	10	7.4	7	0.4
0	10.5	7.7	7.35	0.35
0	11	8	7.7	0.3
0	11.5	8.2	8.05	0.15
0	12	8.4	8.4	0
0	12.5	8.6	8.75	-0.15
0	13	8.85	9.1	-0.25
0	13.5	9.1	9.45	-0.35
0	14	9.45	9.8	-0.35
0	14.5	9.95	10.15	-0.2
0	15	10.5	10.5	0
0.5	-15	-9	-9	0
0.5	-14.5	-8.5	-8.65	-0.15
0.5	-14	-8.05	-8.3	-0.25
0.5	-13.5	-7.7	-7.95	-0.25
0.5	-13	-7.5	-7.6	-0.1
0.5	-12.5	-7.25	-7.25	0
0.5	-12	-7	-6.9	0.1
0.5	-11.5	-6.75	-6.55	0.2
0.5	-11	-6.55	-6.2	0.35
0.5	-10.5	-6.3	-5.85	0.45
0.5	-10	-5.95	-5.5	0.45
0.5	-9.5	-5.45	-5.15	0.3

0.5	-9	-4.85	-4.8	0.05
0.5	-8.5	-4.35	-4.45	-0.1
0.5	-8	-4	-4.1	-0.1
0.5	-7.5	-3.75	-3.75	0
0.5	-7	-3.5	-3.4	0.1
0.5	-6.5	-3.3	-3.05	0.25
0.5	-6	-3.05	-2.7	0.35
0.5	-5.5	-2.8	-2.35	0.45
0.5	-5	-2.4	-2	0.4
0.5	-4.5	-1.8	-1.65	0.15
0.5	-4	-1.3	-1.3	0
0.5	-3.5	-1	-0.95	0.05
0.5	-3	-0.75	-0.6	0.15
0.5	-2.5	-0.45	-0.25	0.2
0.5	-2	-0.1	0.1	0
0.5	-1.5	0.5	0.45	0.05
0.5	-1	1	0.8	0.2
0.5	-0.5	1.25	1.15	0.1
0.5	0	1.5	1.5	0
0.5	0.5	1.7	1.85	-0.15
0.5	1	2.05	2.2	-0.15
0.5	1.5	2.7	2.55	0.15
0.5	2	3.15	2.9	0.25
0.5	2.5	3.4	3.25	0.15
0.5	3	3.65	3.6	0.05
0.5	3.5	3.85	3.95	-0.1
0.5	4	4.2	4.3	-0.1
0.5	4.5	4.8	4.65	0.15
0.5	5	5.3	5	0.3
0.5	5.5	5.6	5.35	0.25
0.5	6	5.85	5.7	0.15
0.5	6.5	6.1	6.05	0.05
0.5	7	6.3	6.4	-0.1
0.5	7.5	6.55	6.75	-0.2
0.5	8	6.8	7.1	-0.3
0.5	8.5	7.25	7.45	-0.2
0.5	9	7.85	7.8	0.05
0.5	9.5	8.35	8.15	0.2
0.5	10	8.8	8.5	0.3
0.5	10.5	9.1	8.85	0.25
0.5	11	9.35	9.2	0.15
0.5	11.5	9.55	9.55	0
0.5	12	9.8	9.9	-0.1
0.5	12.5	10.05	10.25	-0.2
0.5	13	10.3	10.6	-0.3
0.5	13.5	10.5	10.95	-0.45
0.5	14	10.9	11.3	-0.4
0.5	14.5	11.4	11.65	-0.25
0.5	15	12	12	0
1	-15	-7.45	-7.5	-0.05
1	-14.5	-7	-7.15	-0.15
1	-14	-6.55	-6.8	-0.25
1	-13.5	-6.2	-6.45	-0.25

1	-13	-5.95	-6.1	-0.15
1	-12.5	-5.7	-5.75	-0.05
1	-12	-5.5	-5.4	0.1
1	-11.5	-5.3	-5.05	0.25
1	-11	-5.1	-4.7	0.4
1	-10.5	-4.8	-4.35	0.45
1	-10	-4.45	-4	0.45
1	-9.5	-3.95	-3.65	0.3
1	-9	-3.35	-3.3	0.05
1	-8.5	-2.8	-2.95	-0.15
1	-8	-2.45	-2.6	-0.15
1	-7.5	-2.15	-2.25	-0.1
1	-7	-1.9	-1.9	0
1	-6.5	-1.7	-1.55	0.15
1	-6	-1.5	-1.2	0.3
1	-5.5	-1.15	-0.85	0.3
1	-5	-0.75	-0.5	0.25
1	-4.5	-0.05	-0.15	-0.1
1	-4	0.35	0.2	0.15
1	-3.5	0.65	0.55	0.1
1	-3	0.85	0.9	-0.05
1	-2.5	1.05	1.25	-0.2
1	-2	1.45	1.6	-0.15
1	-1.5	2.1	1.95	0.15
1	-1	2.55	2.3	0.25
1	-0.5	2.8	2.65	0.15
1	0	3	3	0
1	0.5	3.2	3.35	-0.15
1	1	3.55	3.7	-0.15
1	1.5	4.2	4.05	0.15
1	2	4.65	4.4	0.25
1	2.5	4.9	4.75	0.15
1	3	5.1	5.1	0
1	3.5	5.3	5.45	-0.15
1	4	5.7	5.8	-0.1
1	4.5	6.3	6.15	0.15
1	5	6.8	6.5	0.3
1	5.5	7.1	6.85	0.25
1	6	7.35	7.2	0.15
1	6.5	7.55	7.55	0
1	7	7.75	7.9	-0.15
1	7.5	8	8.25	-0.25
1	8	8.3	8.6	-0.3
1	8.5	8.75	8.95	-0.2
1	9	9.35	9.3	0.05
1	9.5	9.9	9.65	0.25
1	10	10.3	10	0.3
1	10.5	10.6	10.35	0.25
1	11	10.85	10.7	0.15
1	11.5	11.1	11.05	0.05
1	12	11.3	11.4	-0.1
1	12.5	11.5	11.75	-0.25
1	13	11.7	12.1	-0.4

1	13.5	12	12.45	-0.45
1	14	12.4	12.8	-0.4
1	14.5	12.95	13.15	-0.2
1	15	13.5	13.5	0
1.5	-15	-6	-6	0
1.5	-14.5	-5.4	-5.65	-0.25
1.5	-14	-4.9	-5.3	-0.4
1.5	-13.5	-4.5	-4.95	-0.45
1.5	-13	-4.2	-4.6	-0.4
1.5	-12.5	-3.95	-4.25	-0.3
1.5	-12	-3.8	-3.9	-0.1
1.5	-11.5	-3.6	-3.55	0.05
1.5	-11	-3.35	-3.2	0.15
1.5	-10.5	-3.1	-2.85	0.25
1.5	-10	-2.8	-2.5	0.3
1.5	-9.5	-2.4	-2.15	0.25
1.5	-9	-1.85	-1.8	0.05
1.5	-8.5	-1.15	-1.45	-0.3
1.5	-8	-0.7	-1.1	-0.4
1.5	-7.5	-0.35	-0.75	-0.4
1.5	-7	-0.1	-0.4	-0.3
1.5	-6.5	0.05	-0.05	0
1.5	-6	0.25	0.3	-0.05
1.5	-5.5	0.55	0.65	-0.1
1.5	-5	0.9	1	-0.1
1.5	-4.5	1.45	1.35	0.1
1.5	-4	2.05	1.7	0.35
1.5	-3.5	2.45	2.05	0.4
1.5	-3	2.65	2.4	0.25
1.5	-2.5	2.85	2.75	0.1
1.5	-2	3.1	3.1	0
1.5	-1.5	3.55	3.45	0.1
1.5	-1	4.2	3.8	0.4
1.5	-0.5	4.55	4.15	0.4
1.5	0	4.75	4.5	0.25
1.5	0.5	4.95	4.85	0.1
1.5	1	5.2	5.2	0
1.5	1.5	5.65	5.55	0.1
1.5	2	6.3	5.9	0.4
1.5	2.5	6.65	6.25	0.4
1.5	3	6.85	6.6	0.25
1.5	3.5	7.05	6.95	0.1
1.5	4	7.35	7.3	0.05
1.5	4.5	7.75	7.65	0.1
1.5	5	8.4	8	0.4
1.5	5.5	8.8	8.35	0.45
1.5	6	9.1	8.7	0.4
1.5	6.5	9.3	9.05	0.25
1.5	7	9.5	9.4	0.1
1.5	7.5	9.7	9.75	-0.05
1.5	8	9.95	10.1	-0.15
1.5	8.5	10.3	10.45	-0.15
1.5	9	10.85	10.8	0.05

1.5	9.5	11.45	11.15	0.3
1.5	10	11.95	11.5	0.45
1.5	10.5	12.3	11.85	0.45
1.5	11	12.6	12.2	0.4
1.5	11.5	12.8	12.55	0.25
1.5	12	13	12.9	0.1
1.5	12.5	13.2	13.25	-0.05
1.5	13	13.45	13.6	-0.15
1.5	13.5	13.7	13.95	-0.25
1.5	14	14	14.3	-0.3
1.5	14.5	14.5	14.65	-0.15
1.5	15	14.95	15	-0.05
2	-15	-4.5	-4.5	0
2	-14.5	-4.2	-4.15	0.05
2	-14	-3.8	-3.8	0
2	-13.5	-3.45	-3.45	0
2	-13	-3.15	-3.1	0.05
2	-12.5	-2.75	-2.75	0
2	-12	-2.4	-2.4	0
2	-11.5	-2.05	-2.05	0
2	-11	-1.7	-1.7	0
2	-10.5	-1.35	-1.35	0
2	-10	-1	-1	0
2	-9.5	-0.65	-0.65	0
2	-9	-0.3	-0.3	0
2	-8.5	0	0.05	-0.05
2	-8	0.35	0.4	-0.05
2	-7.5	0.75	0.75	0
2	-7	1.15	1.1	0.05
2	-6.5	1.5	1.45	0.05
2	-6	1.85	1.8	0.05
2	-5.5	2.25	2.15	0.1
2	-5	2.6	2.5	0.1
2	-4.5	3	2.85	0.15
2	-4	3.3	3.2	0.1
2	-3.5	3.65	3.55	0.1
2	-3	4	3.9	0.1
2	-2.5	4.35	4.25	0.1
2	-2	4.7	4.6	0.1
2	-1.5	5.1	4.95	0.15
2	-1	5.45	5.3	0.15
2	-0.5	5.8	5.65	0.15
2	0	6.15	6	0.15
2	0.5	6.45	6.35	0.1
2	1	6.8	6.7	0.1
2	1.5	7.2	7.05	0.15
2	2	7.55	7.4	0.15
2	2.5	7.9	7.75	0.15
2	3	8.25	8.1	0.15
2	3.5	8.6	8.45	0.15
2	4	8.95	8.8	0.15
2	4.5	9.3	9.15	0.15
2	5	9.65	9.5	0.15

2	5.5	9.95	9.85	0.1
2	6	10.3	10.2	0.1
2	6.5	10.65	10.55	0.1
2	7	10.95	10.9	0.05
2	7.5	11.3	11.25	0.05
2	8	11.65	11.6	0.05
2	8.5	12	11.95	0.05
2	9	12.3	12.3	0
2	9.5	12.65	12.65	0
2	10	13	13	0
2	10.5	13.35	13.35	0
2	11	13.7	13.7	0
2	11.5	14.05	14.05	0
2	12	14.4	14.4	0
2	12.5	14.75	14.75	0
2	13	15.15	15.1	0.05
2	13.5	15.45	15.45	0
2	14	15.8	15.8	0
2	14.5	16.2	16.15	0.05
2	15	16.5	16.5	0

APPENDIX C - PUBLICATIONS

The following technical papers relate directly to the work described in this thesis and have been published, or are accepted for publication.

1. Polkinghorne M.N., Roberts G.N., Burns R.S. and Randolph W.A "A Review of Autopilots and Associated Control Simulation Techniques." SCS Multiconference, Copenhagen, 1991.

2. Polkinghorne M.N., Burns R.S. and Roberts G.N. "A Fuzzy Autopilot for Small Vessels." Proc. 2nd Int. Conference Modelling and Control of Marine Craft, Southampton, pp 349-362, 1992.

3. Polkinghorne M.N., Roberts G.N. and Burns R.S. "Small Marine Vessel Application of a Fuzzy PID Autopilot." Proc. 12th IFAC World Congress, Sydney, Australia, Vol. 5, pp 409-412, 1993.

4. Polkinghorne M.N. Burns R.S. and Roberts G.N. "The Implementation of a Fuzzy Logic Marine Autopilot." Proc. IEE Conference Control 94, Warwick, Vol. 2, pp 1572-1577, 1994.

5. Polkinghorne M.N., Roberts G.N., Burns R.S. and Winwood D. "The Implementation of Fixed Rulebase Fuzzy Logic to the Control of Small Surface Ships." IFAC Journal Control Engineering Practice, Accepted for Publication During 1994.

A REVIEW OF AUTOPILOTS AND ASSOCIATED CONTROL SIMULATION TECHNIQUES

M.N.Polkinghorne
Dept Mechanical Eng
Polytechnic South West
Plymouth PL4 8AA, UK

G.N.Roberts
Control Eng Dept
RNEC Manadon
Plymouth PL5 3AQ. UK

R.S.Burns
Dept Mechanical Eng
Polytechnic South West
Plymouth PL4 8AA. UK

W.Randolph
Marinex Industries Ltd
Upton Poole
BH16 5SJ.UK

ABSTRACT

Autopilots are investigated from the early versions to the classical PID controllers in common use today. Several modern techniques have been implemented in order to improve performance, these include Self-Tuning, Model Reference and Fuzzy Logic. Having reviewed the current state of the art in this field comments are made on potential new areas of interest, these being Neural Networks and H∞.

INTRODUCTION

Steering a ship has over the centuries been the responsibility of the helmsman. Although a large portion of the task requires skill and judgement, others are merely time consuming and tedious, especially when a constant course is required for long periods.

In the 1920's automation of the ship steering process began. As technology has advanced, then so has the composition of the autopilots, and thus their performance and competence in the range of sea-keeping roles has increased.

The majority of autopilots have fixed parameters that meet specified conditions. When a change in these conditions occurs, for example, an alteration in sea state, speed, or depth of water, then the parameter settings may no longer be ideal and could require adjustment if performance is to be maintained at a required level.

Limited alterations may be achieved by the mariner, but this relies on his judgement. Even so, ideal parameter settings are not obtained, only an improved approximation of the required values. It would prove advantageous to have an autopilot that is intelligent in operation and can adapt to new conditions in an effort to maintain optimum performance at all times. To this aim, the current state of technological advance of ship autopilot design is examined.

EARLY AUTOPILOTS

As early as 1922 the main factors for automatic ship control for maintaining a course were specified in a paper (Sperry 1922). The amount of rudder action required to counter yaw was found to differ between ships. It was also highlighted that currents,wind and waves greatly effect the control and performance of a vessel.

The action of the helmsman was analysed to identify its components with the aim of minimising these by the automatic control system.

It was found that there would be an 'easing off' period of the rudder before a counter rudder action was imposed to prevent overshoot of the desired course. Thus the helmsman was controlling the course by the anticipation of the vessels response. The resulting system was an application of the gyrocompass and by 1932 this had been installed on over 400 ships.

Also in that year Minorsky compiled a paper on ship control where he produced an analysis of a ship turning (Minorsky 1922). Minorsky also showed that the ship's acceleration contained both angular and uniform turn components, there being a gradual replacement of angular acceleration by uniform turn as the process progressed. To initiate a turn he identified three main torques, these being External (D)eg. wind, waves, and propellers, Rudder ($C_{(p)}$) and Ship resistance (-B). Thus by taking A to equal the effective moment of inertia of the ship, then:

$$A \frac{d^2e}{dt^2} = -B \frac{de}{dt} - C_{(p)} + D \qquad \ldots 1$$

therefore,

$$A \frac{d^2e}{dt^2} + B \frac{de}{dt} + C_{(p)} = D \qquad \ldots 2$$

This led to the proposal of a set of control equations which could solve the needs of an automatic steering system to differing degrees. By means of the control laws Minorsky (1922) and the work by Sperry (1922) the basis was produced for the simple course-keeping operations of the early autopilots, using a low gain to prevent oscillations.

CLASSICAL AUTOPILOTS

Until about 1950 proportional autopilots were used. The early autopilots developed into the three term controllers, using Proportional,Integral and Derivative (PID) control, which have been widely used across the world. Since the controller is tuned only to a specific set of conditions, it was expected that mariners would make any parameter adjustments to their PID autopilots as required due to environmental, or speed variations. So to this aim a range of suitable terminology was developed. Typical autopilot arrangements thus consisted of Proportional Control (Rudder Action), Integral Action (Automatic Permanent Helm), Derivative Action (Counter Rudder), Limit of Rudder Movement (Rudder Limit) and Dead-Band Width (Weather).

The rudder limit prevented rudder movement outside of a specified range in order to limit the induced roll angle (Mort 1983). The dead-band reduced high frequency rudder operation by imposing a delay, before counteracting measures could be taken. Thus wear on the steering gear could be reduced. Also used was a 'kick' that initiated rudder movement once the dead-band had been exceeded.

The simple proportional controllers were of the form:

$$\delta = K_1 \Psi_e \qquad \ldots 3$$

K_1 could be adjusted to obtain the required results i.e for different environmental conditions.

Even with the improvements of dead zone and kick, there was a tendency for this type of autopilot to overshoot. To overcome this a 'derivative of heading error' term was introduced ,i.e

$$\delta = K_1 \Psi_e + K_2 \dot{\Psi}_e \qquad \ldots 4$$

Also to be introduced was the integral of the heading error term. This allowed an improvement in course during steady disturbances, thus:

$$\delta = K_1 \Psi_e + K_2 \dot{\Psi}_e + K_3 \int \Psi_e \, dt \qquad \ldots 5$$

The equation now describes the classical three term (PID) controller. To counteract any possibility of a sluggish response due to the integrator, a further acceleration term could also be included:

$$\delta = K_1 \Psi_e + K_2 \dot{\Psi}_e + K_4 \ddot{\Psi}_e + K_3 \int \Psi_e \, dt \qquad \ldots 6$$

Either of these final terms were capable of producing a good set of steering characteristics. To prevent the previously mentioned high frequency rudder movements that cause excessive wear, a more applicable solution to dead zone was required. Motora applied a low-pass filter (Motora 1953). Rydill suggested that this may reduce stability and thus put forward the quadratic delay technique (Rydill 1958) forming a controller transfer function of :

$$\frac{\delta_{(s)}}{\Psi_{(s)}} = \frac{K_5 (1 + s)}{(1 + K_6 s + K_7 s^2)} \qquad \ldots 7$$

This would provide a sharp reduction in rudder movements at high frequencies.

The PID autopilot has limitations, eg the dead-band suppresses small amplitude heading errors, which thus reduces accuracy. In addition the combination of dead-band and integral action can produce a limit cycle oscillation about the desired heading causing an increase in the vessel's resistance.

It is clear that problems are apparent during course-keeping for the classical PID type autopilot. This is further shown in the course-changing role when accuracy of steering is essential because of the need to avoid obstacles, traffic, etc and due to environmental changes e.g depth, width of channel and speed.

It is also a major issue that the mariner either does not understand, or bother to change, the controller parameter settings. In normal conditions the controller is probably struggling to produce reasonable results under this handicap. When disturbances etc suddenly change, i.e rounding a headland, then it is clear that a PID controller will perform in a less than satisfactory manner. In response to this, a variety of new techniques have been investigated.

MODERN AUTOPILOT TECHNIQUES

In recent years a selection of modern control techniques have been used to replace the PID controller in an attempt to improve the autopilot performance. For this application it is useful to have a controller that is robust, ie. maintains stability as ship parameters vary.

For a vessel under automatic control the maintenance of stability is essential. The need for optimal parameter values is apparent when the auxiliary characteristics of the ship are examined, these are accuracy (derivation from derived heading), economy (minimum fuel consumption, minimum time), navigational aspects and mechanical wear on steering gear. Propulsion losses whilst steering a ship also occur. Minimum steering is required in order to keep the losses as low as possible. It is stated (Clarke 1982) that there is a significant increase in the effect on the ship's motion by induced yawing due to external wave and wind action, causing ships drag to increase, speed to be reduced and a long sinusoidal path to be taken by the vessel thus further reducing the down track speed.

By correcting using rudder, the autopilot actually increases the drag. These effects were minimised (Koyama 1967) by the correct selection of values in a PD controller. The parameters of mean square heading error Ψ_e^2 and mean square angle δ^2 were monitored and used in the performance index:

$$J = \overline{\Psi_e^2} + \lambda \overline{\delta^2} \qquad \ldots 8$$

Where λ is approximately equals 8 for a cargo ship or 0.2 (Koymam 1967) and (Norrbin 1972) respectively. It was suggested by (Motora and Koyama 1968) that a cost function of the form

$$J = \frac{1}{T} \int_0^T (\Psi_e^2 + \lambda \delta^2) dt \qquad \ldots 9$$

should be employed where λ is between 4 and

8. Norrbin contradicts this with $\lambda = 0.1$ for large ships, however (Van Amerongen and Van Nauta Lemke 1978) suggest $\lambda = 10$.

Using the Bore 1 type vessel (Astrom et al 1975) found the results that for $\lambda = 0.1$ there was a fast response, impossible rudder angles were demanded, whilst for $\lambda = 10$, the response was sluggish with inaccurate steering. Given the variation of findings there is clearly scope for further research.

Whilst investigating fuel savings (Clarke 1980) developed the cost function:

$$F = a\overrightarrow{\psi_e^2} + \overleftarrow{br^2} + c\overleftarrow{\delta^2} \qquad \ldots 10$$

where a, b, c were dependant on ship type, propeller type, engine control systems and the rudder geometry. In addition Clarke also required equations of motion, description of sea and wind disturbances which change due to ship loading, speed, water depth etc.

Clearly the need for optimum settings of parameters is important. With constantly changing environmental factors it would appear to be a desirable improvement if the autopilot could adapt itself to current conditions, whatever they may be thus finding new optimum values as necessary. The modern autopilot techniques are therefore attempting to continually update their controller parameters, the main developements being in the areas of self-tuning, model reference and fuzzy logic controllers.

In the area of multivariable optimal control errors in position, heading and speed are taken into account by obtaining a global optimum. (Burns 1990).

Self-Tuning Controller

Work on Self Tuning Controllers (STC) started with (Astrom and Wittenmark 1973). It was Kallstrom who applied various styles of controller to solving the problems associated with ship steering. The controller was designed to adapt to variations in ship velocity by means of velocity scheduling, thus producing a faster adaption process. Knowledge was required of the ships steering parameters when speed was varied. Modifications were required to cope with large heading changes on very large vessels. A different cost function (Tiano and Brink 1981) was applied to the STC as shown :

$$J = E\{(Y_{t+k} - W_t)^2 + \lambda U_t^2\} \qquad \ldots 11$$

so in course keeping mode $W_t \to 0$ and in course changing mode $\lambda = 0$ providing a fairly good degree of autopilot performance.

The self tuning regulator ideas (Astrom and Wittenmark 1973) designed to regulate an unknown system when subjected to noisy disturbances with the (Clarke and Gawthrop 1975) algorithm was employed (Mort 1983). This used the principles of recursive least squares estimation combined with performance index minimisation by the control law .

$$I_1 = E\{Y^2_{t+k}\} \qquad \ldots 12$$

Thus the variance of the system was minimised. The basic algorithm contained the two main limitations that no set point following was included and no penalty on control effect. Important factors to consider if rudder action is to be minimised on the autopilot. Mort employed:

$$I_2 = E\{(Py_{t+k} - Rw_t)^2 + Q^2\} \qquad \ldots 13$$

In practice actual values varied from the optimum ones, but this was overcome by the introduction of a 'forgetting factor'.

The STC reached optimal values in approximately 10-20 samples. Mort found that it compared well with an optimal value with the exception of a small overshoot. As the model order was raised,the response remained stable, however, the overshoot was increased. This could have been overcome by adjusting the weighting factors in the cost function, the simple STC could not perform this task.

The resulting STC did compare favourably with an optimal state feedback controller (with complete knowledge of parameters) and gave satisfactory results. In addition it proved capable of monitoring slowly varying parameters.

Model Reference Controller

For this style of control a model is required which can be placed in parallel or in series with the system. With the series approach, the series model generates the desired response and the control system forces the ship to follow. In the parallel approach the ships actual response and that of the ideal model are compared to give an error signal. When changes occur due to environmental factors the error signal is utilised to adjust the controller parameters. Early versions used the sensitivity approach whilst today the Liapunov theory, (Landau 1974), is applied.

Initially the results were inadequate when subjected to noise due to sea state. Thus high frequency rudder action was generated. The Liapunov approach was used (Van Amerongen 1975) which assumes that the system and the reference model are the same. For a difference in variables between the model and the system, then the parameters are adjusted to minimise this.

Using a linear model and system this method was acceptable without noise subjection, but required a low-pass filter when in a noisy sea, ie. when disturbances were frequent.

When compared against optimal control values it was found that the optimum method was better for long voyages where fuel could be saved and time for transfer function identification was possible, however the model reference system had improved steering in coastal waters where the behaviour of the ship could vary swiftly, and large course alterations were required. The course keeping success of the model reference controller was poor because disturbances were not taken into account explicitly, (Kallstrom 1979).

Fuzzy Logic Controller

Fuzzy logic is a useful means of control without the use of a rigid mathematical model. The principles of fuzzy logic are well explained in a tutorial paper (Sutton and Towill 1985). The fuzzy logic approach attempts to design a controller based on the often erratic and inconsistant actions of the human operators experience. In addition a human response may be due to a complex pattern of unmeasurable variables e.g colour.

All these factors will lead a human to a decision. Using conventional techniques these values would need to be presented in a quantitative form which is not practical. Fuzzy sets can be used to directly describe these details, therefore overcoming these problems. This technique was proposed by (Zadeh 1973).

After the first real application (Mamdani and Assilian 1975), there has been a tendency to employ the fuzzy technique to 'model linguistic expressions of human control'. In conventional set theory 0 equals 'not a member' and 1 equals 'is a member'. In fuzzy logic, sets may be described by a number between 0 and 1, giving a full member of the set, and a non member, but also a range of partial members with various degrees of membership. Since this is far less precise than the conventional approach, it is more accurate since shades of importance may be included. Examples of fuzzy sets could be positive big, positive medium or negative small and could be used to describe yaw error and change of yaw error in terms of fuzzy values. Rules of the form If <Condition> then <Action> are formed into a rule base. The actions contained within the rule base corresponds to the output window. The fuzzy values indicate the fuzzy actions required which are in turn transformed into a non-fuzzy output using a minimisation operation and then the centre of area method. Since a rule for every situation is not feasible, then rules may be composed due to inference.

An autopilot designed with fuzzy sets was attempted (Van Amerongen 1977) which proved very robust to parameter variations. When compared to PID, both controllers performed similarly when optimally adjusted. After the addition of noise, the fuzzy controller performed significantly better, and with fewer rudder calls.

The fuzzy controller is not adaptive and has no learning capability. The self organising controller is a further development and attempts to implement the fuzzy rules within an adaptive environment.

Self-Organising Controller

The Self Organising Controller (SOC) is based upon Zadeh's fuzzy logic with the addition of a learning mechanism to provide adaption. The SOC uses a performance index such as (Sugiyama 1988) describes, to monitor the controller's performance and to adjust the control rules when performance is low.

The performance index contains zero elements when response is satisfactory, and increasing values corresponding to decreasing performance. It is the size of these non-zero elements that controls the amount of rule modification, ie the worse the response then the greater the adjustment.

The rules responsible for the response are identified before modification takes place, leading to the rule base being customised to maintain satisfactory control.

A self organising controller (SOC) with a fuzzy logic PID approach was used (Jess 1990) to control the yaw of a warship. The SOC has been shown as analogous to a PID controller since it employs Gain error (GE), Gain change in error (GCE), and Gain change in change in error (GCCE), equivalent to P,I and D, as variable gains used to modified any error signals. A few applications achieved rule convergence, ie the rule modifier updated the fuzzy rule base so that performance requirements were achieved. When compared to the STC from (Mort 1983), Jess' controller was slower in response, but minimal overshoot and rudder demand were produced. A negative initial excursion was experienced for large values of (GCCE), small values giving poor damping, although this could be overcome by a variable gain algorithm. Additional investigations into the use of SOC's for roll control have been carried out, (Sutton et al 1990).

CURRENT ADVANCES IN AUTOPILOT DESIGN

Two areas currently causing interest in the field of autopilot design are Neural Networks and H∞.

Neural Networks

This principle is an attempt to simulate the human brain using a network of nodes with axons and dendrites. (inputs and outputs) and associated weighting values.

Work has been undertaken to develop auto tuning controllers (Claudio et al 1991) and maritime applications (Yamata 1990) and are now being found. Possibilities for autopilot control is now under investigation at Polytechnic South West, UK.

H∞

The principles of H∞ were proposed (Zames 1981) and extended (Grimble 1987). When used for autopilot design Fairbairn 1990) the initial results found that for course changing a good response was obtainable, even when subjected to disturbances of wind and waves. In course-keeping mode rudder activity was reduced but heading accuracy suffered due to wave disturbance. Further developments for non-linear models are proposed.

CONCLUSIONS

It is clear that to improve on the classical PID autopilots is advantageous if rudder action, down track time and fuel usage are to be minimised. An autopilot design that does not require an accurate vessel model, and has a learning ability could prove an invaluable asset in the search for an intelligent autopilot. To this aim development of the modern control techniques discussed in this report with application in up to 6 degrees of freedom must be encouraged, if the current development rate of new autopilots is to be maintained.

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NOMENCLATURE

E - Expectation Operator
J - Cost Function Term
K - System Time Delay
$K_1, K_2, K_3, K_4, K_5, K_6, K_7$ - Gain Constants
P,Q,R - Polynomials in Z^{-1}
r - Rate of Turn
U_t - Control Input
W_t - Set Point
X - Weighting Factor
Y - System Output
δ - Rudder
Ψ - Yaw
Ψ_e, e - Yaw Error
$\dot{\Psi}_e$ - Rate of Change of Yaw Error

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A Fuzzy Autopilot For Small Vessels

M N Polkinghorne*, R S Burns* and G N Roberts+

*Polytechnic South West, Drake Circus, Plymouth.
+Royal Naval Engineering College, Manadon, Plymouth.

ABSTRACT

A fuzzy logic controller is developed for a small maritime vessel. Responses in both course-changing and course-keeping modes are investigated and compared to a classical PID autopilot over a typical range of weather conditions.

1. INTRODUCTION

In the 1920's automation of the ship steering process began. With technological advancements the achievable performance and competence in the range of sea-keeping roles has increased.

The majority of current autopilots are based on the Proportional plus Integral plus Derivative (PID) controller and have fixed parameters that meet specified conditions. In practice maritime vessels are non-linear systems. Any changes in speed, water depth or mass may cause a change in dynamic characteristics. Additionally the severity of the weather will alter the disturbance effects caused by wind, waves and current.

Despite the PID autopilot having settings to adjust course and rudder deadbands [1] to compensate for vessel or environmental changes, the resulting performance is often far from optimal, causing excess fuel consumption and rudder wear. These effects are particularly apparent in small vessels whose sensitivity to disturbances and controller setting is far greater than that with large ships. Modern control techniques of H^∞ [2], Optimality [3], Self-tuning [4], [5], and Model Reference [6] have been applied to such vessels in attempts to improve performance.

Fuzzy logic controllers are thought to be robust enabling them to cope with changes arising in ship dynamics and sea conditions. Based on Fuzzy set theory as proposed by Zadeh [7] they have found maritime applications including submersibles [8], ships [9], [10] and torpedoes [11].

Of the autopilots in use today, a significant proportion can be found on small vessels. Given their increased susceptibility to disturbances, it is important to discover if the fuzzy controller designs applied to large vessels [10] can successfully be utilised on small ships, and whether such a controller can then operate with equal success over the range of typical disturbance conditions.

In this paper the application of fuzzy logic control in the development of an autopilot for small vessels is presented, with comparisons made to a tuned PID autopilot.

2. VESSEL AND DISTURBANCE MODELS

Models for both vessel dynamics in yaw, and for the disturbances and wave, wind and current had to be generated as a pre-requisite for fuzzy logic controller design and evaluation.

2.1 Yaw dynamics

A pc based Runge-Kutta integration routine was utilised for the model simulation. This investigation used a Nomoto model [12] of the form:

$$\frac{\psi(s)}{\delta(s)} = \frac{0.3848(s+0.603)}{s(s+1.656)(s+0.3874)} \tag{1}$$

where: $\psi(s)$ = Yaw (output of vessel model).

$\delta(s)$ = Actual rudder plus disturbance effects (input to vessel model).

The model of the 11 metre vessel for a speed of 8 knots was derived from hydrodynamic coefficients. Rudder dynamics were modelled as a linear function with a time constant of 1 second and saturation limits of $\pm 20^{\circ}$.

2.2 Wave disturbances

In order to simulate ship behaviour with any degree of realism it is essential to include disturbance effects.

In any one place on the sea's surface a combination of waves will be present, all with different frequencies, heights and phase relationships. This combination for a fully developed sea can be described by a wave energy density spectrum. As a simple case all wave components may be regarded as travelling in a single direction giving a one dimensional sea. Pierson and Moskowitz [13] developed such a wave spectrum [Figure 1] based on the wind speed at 19.5 metres above the sea's surface and characterised for differing weather conditions by the significant wave height (swh), ie. the average height of the highest one third of waves.

$$S_{PM}(\omega) = \frac{A}{\omega^5} e^{-B/\omega^4} \qquad (2)$$

where: S_{PM} = spectral density ($m^2 rad^{-1} s$)
A = $0.0081g^2$
B = $3.11/swh^2$
g = gravitational acceleration.
ω = frequency of encounter $rads^{-1}$

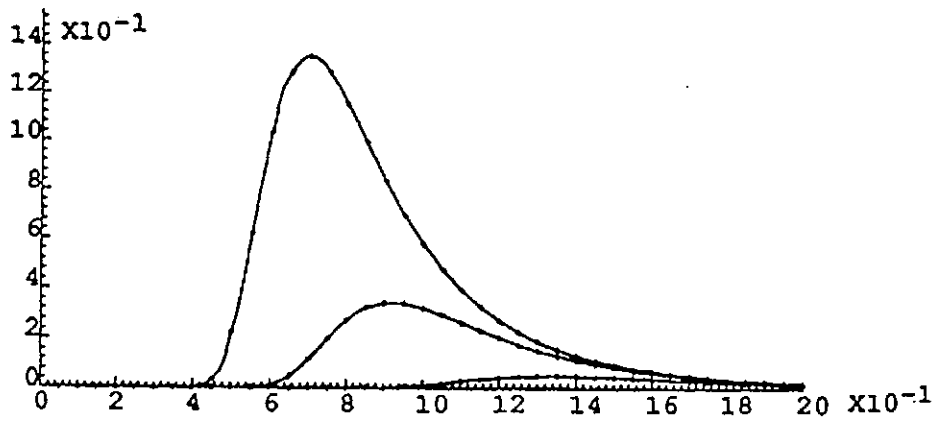

Figure 1: Wave Energy Density Spectrums

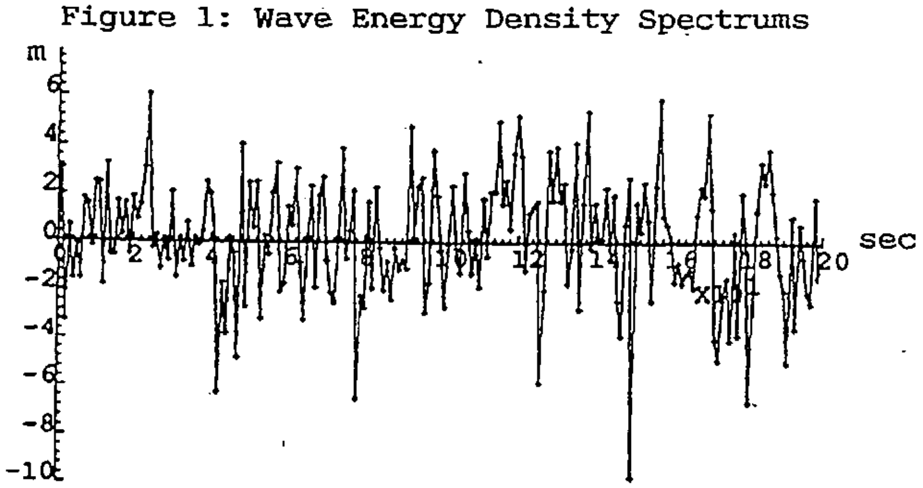

Figure 2: Wave Time History - Sea State 5

Based on the spectrums shown in Figure 1, a wave time history with zero mean for a given sea state code was generated using an Inverse Discrete Fourier Transform [Figure 2]. Table 1 was generated using sea state information and wind data from Sutton et al [15].

Table 1. Data For Sea State Codes

Sea State Code	Significant Wave Height (m)	Mean Wind Speed (ms^{-1})
1	0.05	1.51
2	0.30	3.70
3	0.88	6.34
4	1.88	9.25
5	3.25	14.75
6	5.00	15.11
7	7.50	18.50
8	11.50	22.91
9	>14.00	>23.00

By relating the sea state and wind in this manner it is possible to deduce the mean wind speed for a particular sea state.

2.3 Wind and current disturbance

Both the wind and current disturbances may be considered to act as a constant disturbance with a gusting factor by using a Gauss-Markov function, as developed by Burns [14], of the form:

$$U(k+1) = AU(k) + BW(k) \tag{3}$$

where:
$A = e^{T/T_c}$
T = 1 sec (sampling time)
T_c = 10 sec (Break frequency of 0.0159Hz)
$B = 1-A$
U = Present value of gust (ms^{-1})
W = Gaussian random process gusting to ±20% of mean value.

The deterministic and stochastic elements were combined for wind and for current, [Figure 3].

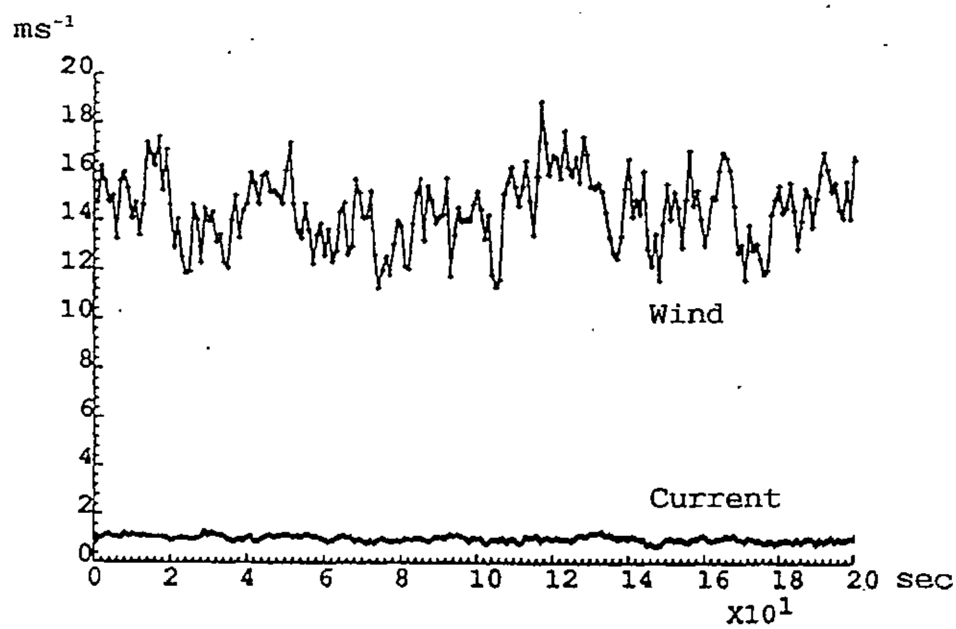

Figure 3: Wind and Current Time Histories - Sea State 5

Based on the experience of an actual autopilot manufacturer, it was decided that the worst weather conditions that a small vessel would expect to be at sea, under autopilot control, would be sea state 5. The simulation conditions relating to sea state 5, ie. a swh of 3.25m, a wind speed of $14.75ms^{-1}$ and a current of $1.0ms^{-1}$, were therefore used for disturbance purposes in this investigation.

The forces and consequently the moments produced for each disturbance were scaled relative to the rudder moment and summed with the rudder input.

3. AUTOPILOT CONTROL

The autopilot may be considered to act in two modes, namely course-changing and course-keeping. The requirements for these two modes are:

Course-Changing - to reduce the yaw heading error with a minimum overshoot, settling time and rudder action.

Course-Keeping - to maintain the desired course with a minimum yaw heading error, rudder action and number of rudder calls, given the application of disturbances.

The final autopilot design requires both these modes to operate together. However, to aid this investigation the actions have been separated so that each mode may be considered individually.

3.1 PID autopilot

The classical PID autopilot used was of the form:

$$G_{c(s)} = K_p[1+\frac{1}{T_i s} + T_d s] \tag{4}$$

where: K_p = Proportional Gain
T_i = Integral Action
T_d = Derivative Action

For comparison with a Fuzzy controller, the PID autopilot was tuned for this particular vessel. In practice the autopilot is tuned for an approximate length of boat. The parameter settings then remain constant with the autopilot changing from course-changing to course-keeping modes when the yaw heading error falls within a specified band. The size of the band is set by the user and depends on the weather.

To allow consistent comparison between the PID and fuzzy logic designs, the possible deadbands and weather settings were ignored. The PID controller was tuned to minimise the root mean square (RMS) yaw error with optimum controller parameters being K_p = 1.6, T_d = 2.0 seconds and T_i = 100 seconds for course-changing, [Figures 4 & 5], and K_p = 12, T_d = 10 seconds and T_i = 0.1 seconds for course-keeping, [Figures 6 & 7].

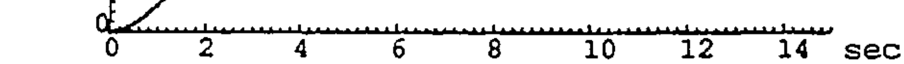

Figure 4: Yaw Response (PID) for 10° Heading Change

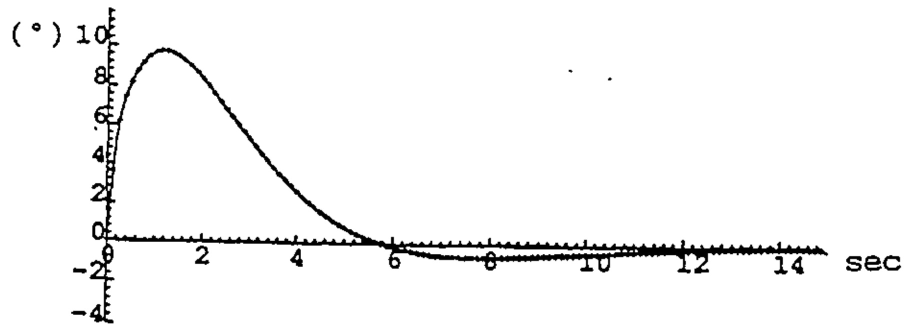

Figure 5: Corresponding Rudder Action

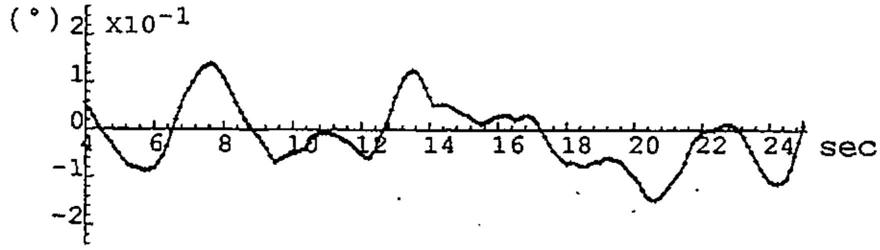

Figure 6: Yaw Response (PID) - Sea State 5

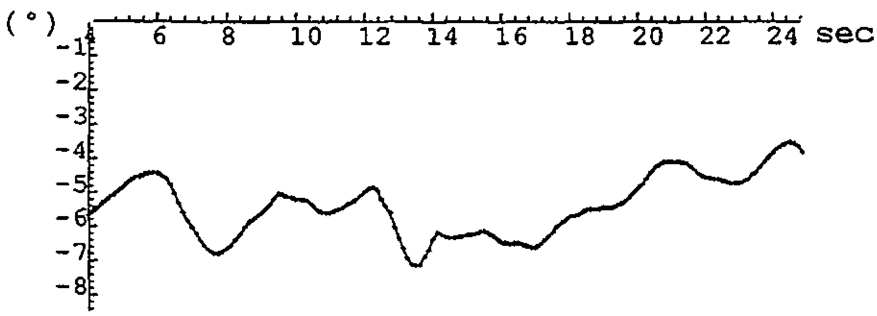

Figure 7: Corresponding Rudder Action

4. FUZZY LOGIC AUTOPILOT DESIGN

The fuzzy logic controller utilised in this investigation is closely related to the work by Farbrother and Stacey [8] with its descendancy traceable through Sutton [16] back to the early work by Van Amerongen et al [9].

The input variables of yaw error and yaw rate are converted to fuzzy values by their associated input windows, each containing seven triangular fuzzy sets [Figures 8 & 9]. These sets are symmetrical in shape about a set point. Each set is given the linguistic label Positive Big (PB), Positive Medium (PM), Positive Small (PS), About Zero (Z), Negative Small (NS), Negative Medium (NM), or Negative Big (NB).

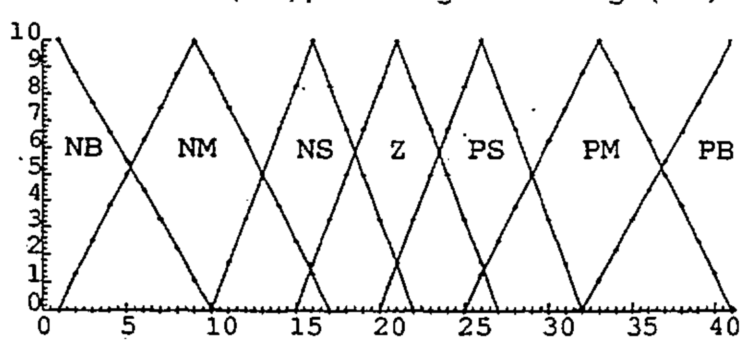

Figure 8: Yaw Error Input Window

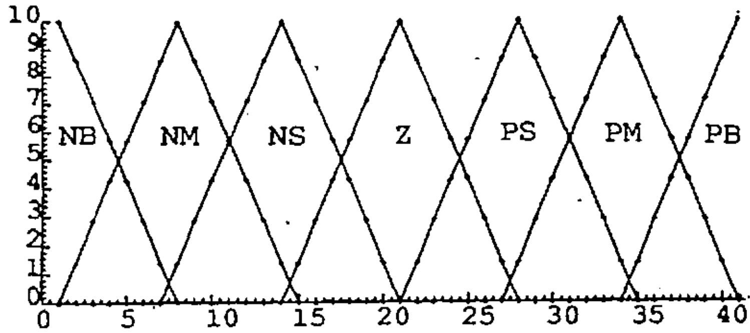

Figure 9: Yaw Error Rate Input Window

The fuzzy logic controller is constructed around a rule base [Figure 10], each rule being of the type:

IF (Condition A) **AND** (Condition B) **THEN** (Action)

ce \ e	NB	NM	NS	Z	PS	PM	PB
NB	NB	NB	NB	NM	Z	PM	PB
NM	NB	NB	NB	NM	PS	PM	PB
NS	NB	NB	NM	NS	PS	PM	PB
Z	NB	NM	NS	Z	PS	PM	PB
PS	NB	NM	NS	PS	PM	PB	PB
PM	NB	NM	NS	PM	PB	PB	PB
PB	NB	NM	Z	PM	PB	PB	PB

Figure 10: Fuzzy Rule Base

The nature of the input windows ensures that several rules may be activated together, the output of each rule being modified by a weighting term. The output window contains seven asymmetrical sets [Figure 11] which due to previous work [8] is known to create a smoother output from the controller. By employing the centre of area method to all the active output sets, a deterministic controller output may be obtained.

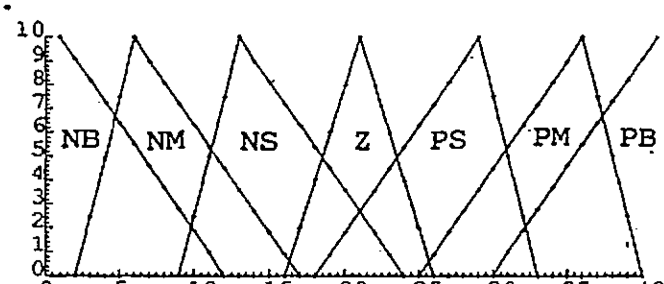

Figure 11: Rudder Output Window

4.1 Course-Changing Fuzzy Logic Autopilot

The window limits for yaw error (e) and rate (ce) were varied to obtain the optimum performance. Output window limits were maintained at ±20° to fully utilise the available rudder movement. The RMS values for both yaw error and rudder action were recorded for analysis.

Based on a step change in yaw of 10°, the fuzzy logic controller was also tuned to minimise the RMS yaw error with final window limits of yaw error ±11.5°, rate $\pm 4.5^{\circ}s^{-1}$ and rudder ±20°, [Figures 12 & 13].

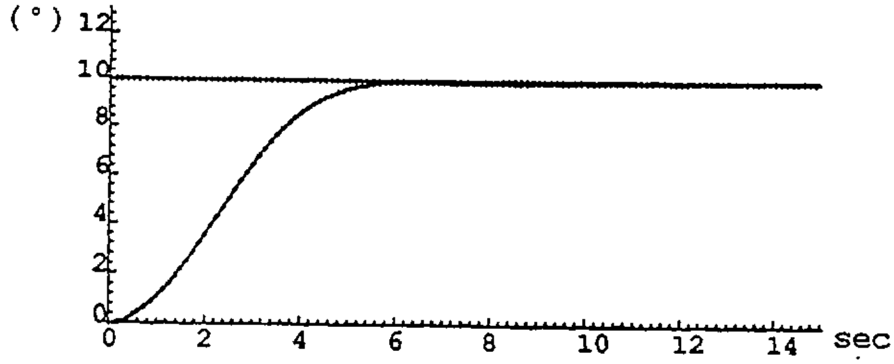

Figure 12: Yaw Response (FUZZY) for 10° Heading Change

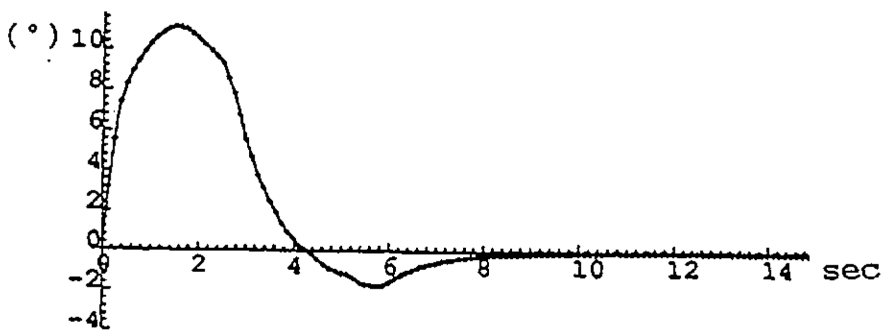

Figure 13: Corresponding Rudder Action

Having established optimum parameters, the controller was subjected to a step change demand in yaw of 30° to indicate the obtainable performance across the typical course-changing envelope. The results are shown in Table 2 where it can be seen that the fuzzy logic controller clearly reduced the RMS yaw error 'across the board' whilst for smaller changes in heading an increase in RMS rudder action was apparent.

Table 2. Course-Changing Results for Fuzzy Logic and PID Autopilots

	PID Controller	Fuzzy Logic Controller	Fuzzy Logic Improvement
Step Size 10°			
RMS Yaw Error (°)	3.65	3.53	+3.3%
RMS Rudder Action (°)	3.79	4.26	-12.5%
Step Size 20°			
RMS Yaw Error (°)	12.51	10.03	+19.8%
RMS Rudder Action (°)	9.21	8.78	+4.7%

4.2 Course-Keeping Fuzzy Logic Autopilot

As with the course-changing autopilot, the window limits for yaw error and rate were adjusted to obtain an optimum value of RMS yaw error. The final window limits with the disturbance inputs of sea state 5 were yaw error ±0.3°, rate $\pm 0.2°s^{-1}$ and rudder ±20°, [Figures 14 & 15].

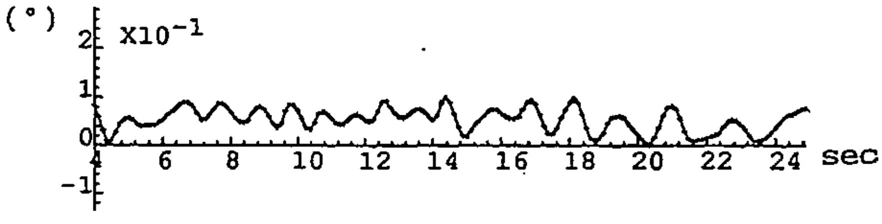

Figure 14: Yaw Response (FUZZY) - Sea State 5

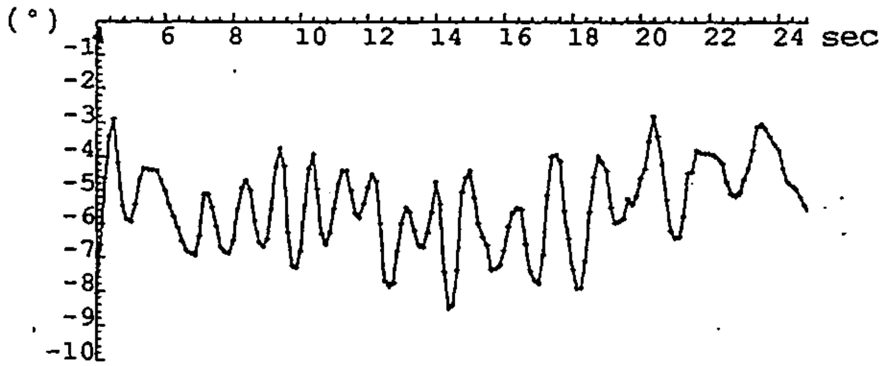

Figure 15: Corresponding Rudder Action

To test the robustness qualities of the fuzzy logic controller over a range of significant operating weather conditions, both the controllers were subjected, without change, to sea state 3 weather conditions, ie. a swh of 0.875m, a wind speed of $6.34ms^{-1}$ and a current of $0.1ms^{-1}$. The results are summarised by Table 3.

Table 3. Course-Keeping Results for Fuzzy Logic and PID Autopilots

	PID Controller	Fuzzy Logic Controller	Fuzzy Logic Improvement
Sea State Code 5			
RMS Yaw Error (°)	0.068	0.059	+12.5%
RMS Rudder Action (°)	5.454	5.579	-2.2%
Sea State Code 3			
RMS Yaw Error (°)	0.022	0.007	+65.0%
RMS Rudder Action (°)	0.671	0.774	+15.0%

For sea state 5 weather conditions the Fuzzy Logic controller proved more successful at minimising the RMS yaw error. Following the application of sea state 3 conditions, the fuzzy autopilot demonstrated a further increase in performance compared to that of the PID autopilot.

5. CONCLUSIONS

The principles of fuzzy logic have been shown to successfully control the yaw response of a small vessel. In both course-changing and course-keeping modes the fuzzy autopilot reduced the RMS yaw error with only a slight rise in RMS rudder action. The output of the fuzzy controller is naturally noisy and could be improved by the addition of a filter which would reduce the RMS rudder action.

The general performance of the fuzzy logic controller has been shown to be superior to the PID autopilot for the constant speed model. The next stage in the investigation is to undertake a comprehensive sensitivity analysis whereby the performance of the fuzzy logic autopilot in course-changing and course-keeping modes will be assessed for suitable variations in vessel dynamic characteristics.

ACKNOWLEDGEMENTS

The authors would like to thank the Marine Technology Directorate (SERC) and Marinex Industries Ltd for support to undertake the investigation into "Modelling and Control of Small Vessels", (Grant Ref Number GR/G21162).

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SMALL MARINE VESSEL APPLICATION OF A FUZZY PID AUTOPILOT

M N Polkinghorne[*], G N Roberts[+] and R S Burns[*]

[*]*University of Plymouth, Drake Circus, Plymouth, PL4 8AA. UK.*
[+]*Royal Naval Engineering College, Manadon, Plymouth, PL5 3AQ. UK.*

Abstract. A fuzzy logic PID controller is developed for a small maritime vessel. Responses in the course-keeping mode are investigated and compared to a classical PID autopilot over a typical range of weather conditions with RMS yaw error and rudder action being utilised to quantify the quality of results obtained.

Key Words. Fuzzy Control; PID Control; Fuzzy PID; Ship Control; Ship Autopilot.

1. INTRODUCTION

During the 1920's automation of the ship steering process began. With advancements in technology the achievable performance and competence in the range of sea-keeping roles has increased.

Most of the current autopilots are based on the Proportional plus Integral plus Derivative (PID) controller and have fixed parameters that meet specified conditions. In practice maritime vessels are non-linear systems. Any changes in speed, water depth or mass may cause a change in dynamic characteristics. In addition the severity of the weather will alter the disturbance effects caused by wind, waves and current.

Typically PID autopilots have settings to adjust course and rudder deadbands (Cetrek Ltd, 1990) to compensate for vessel or environmental changes. Despite this the resulting performance is often far from optimal, causing excess fuel consumption and rudder wear. These effects are particularly apparent in small vessels whose sensitivity to disturbances and controller setting is far greater than that with large ships. Modern control techniques of H^∞ (Fairbairn and Grimble, 1990), Optimality (Burns, 1990), Self-tuning (Tiano and Brink, 1981; Mort and Linkens, 1980), Model Reference (Van Amerongen, 1975) and Neural Networks (Endo *et al*, 1989) have been applied to such vessels in attempts to improve performance.

Fuzzy logic controllers are thought to be robust enabling them to cope with changes arising in ship dynamics and sea conditions. Based on Fuzzy set theory as proposed by Zadeh (Zadeh, 1965) they have found maritime applications including submersibles (Farbrother and Stacey, 1990), ships (Van Amerogen *et al*, 1977; Sutton and Towill, 1985) and torpedoes (Jones *et al*, 1990).

Of the autopilots in use today, a significant proportion can be found on small vessels. Given their increased susceptibility to disturbances, it is important to discover if the fuzzy controller designs applied to large vessels (Sutton and Towill, 1985) and small craft (Polkinghorne *et al*, 1992) can successfully be modified by the addition of an integral action to improve performance when operating over a range of typical disturbance conditions.

In this paper the application of fuzzy logic control in the development of a fuzzy PID autopilot for small vessels is presented, with comparisons made to a tuned PID autopilot.

2. VESSEL AND DISTURBANCE MODELS

As a pre-requisite for the design and evaluation of the fuzzy logic controller, models for both vessel dynamics in yaw, and for the disturbances of wave, wind and current had to be generated.

2.1 Yaw Dynamics

A pc based Runge–Kutta integration routine was utilised for the model simulation. This investigation used a Nomoto model (Nomoto *et al*, 1957) of the form:

$$\frac{\psi(s)}{\delta(s)} = \frac{0.3848(s+0.603)}{s(s+1.656)(s+0.3874)} \quad (1)$$

where: $\psi(s)$ = Yaw (output of vessel model).
$\delta(s)$ = Actual rudder plus disturbance effects (input to vessel model).

The model of the 11 metre vessel for a speed of 8 knots was derived from hydrodynamic coefficients. Rudder dynamics were modelled as a linear function with a time constant of 1 second and saturation limits of ±20°.

2.2 Disturbances Effects

In order to simulate ship behaviour with any degree of realism it is essential to include disturbance effects. Using an energy density spectrum for waves (Pierson and Moskowitz, 1964) and a Gauss–Markov function for both wind and current (Burns, 1984) the maritime disturbances associated with sea states 3,4 and 5 were simulated as described previously (Polkinghorne *et al*, 1992).

The forces and consequently the moments produced for each disturbance were scaled relative to the rudder moment and summed with the rudder input.

3. PID AUTOPILOT CONTROL

The classical PID autopilot used was of the form:

$$G_{c(s)} = K_p[1 + \frac{1}{T_i s} + T_d s] \quad (4)$$

where: K_p = Proportional Gain
T_i = Integral Action
T_d = Derivative Action

For comparison with a Fuzzy controller, the PID autopilot was tuned for this particular vessel. In practice the autopilot is tuned for an approximate length of boat, the parameter settings then remain constant. To allow consistent comparison between the PID and fuzzy logic designs, the possible deadbands and weather settings were ignored. The PID controller was tuned to minimise the root mean square (RMS) yaw error giving due consideration to the resulting rudder response [Fig.1].

The fuzzy logic controller utilised in this investigation is closely related to recent work (Farbrother and Stacey, 1990) with its descendancy traceable (Sutton ,1987) back to the early work (van Amerogen *et al*, 1977). It was shown (Polkinghorne *et al*, 1992) that a fuzzy PD controller could successfully minimise the yaw error of a small vessel. By adjusting the window limits sufficiently to smooth the resulting rudder response a steady–state error caused by the disturbance effects was produced. The historical PD form of the fuzzy controller was therefore extended by the introduction of a parallel integral controller, derived from an idea previously presented (Kwok *et al*, 1991).

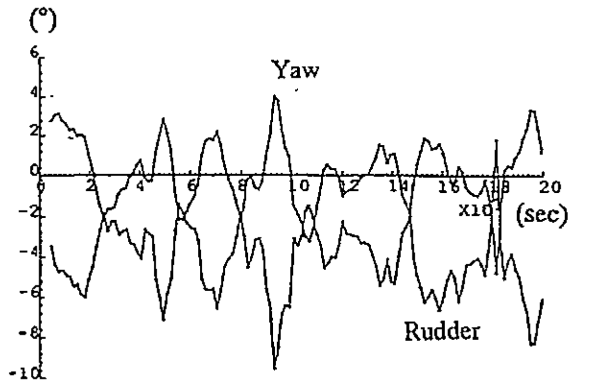

Fig 1. Yaw & Rudder Responses (PID) – Sea State 4

4. FUZZY LOGIC AUTOPILOT DESIGN

In the fuzzy PD controller the input variables of yaw error and yaw rate are converted to fuzzy values by their associated input windows, each containing seven triangular fuzzy sets [Fig.2]. These sets are symmetrical in shape about a set point. Each set is given the linguistic label Positive Big (PB), Positive Medium (PM), Positive Small (PS), About Zero (Z), Negative Small (NS), negative Medium (NM), or Negative Big (NB).

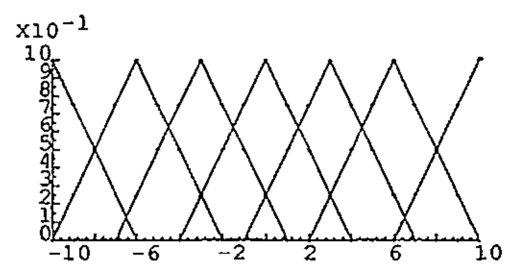

Fig. 2. Fuzzy Input Window

The fuzzy logic PD controller is constructed around a rule base [Table 1], each rule being of the type:

IF (Condition A) **AND** (Condition B) **THEN** (Action)

Table 1: Fuzzy PD Rulebase

CE\E	NB	NM	NS	Z	PS	PM	PB
NB	NB	NB	NB	NM	Z	PM	PB
NM	NB	NB	NB	NM	PS	PM	PB
NS	NB	NB	NM	NS	PS	PM	PB
Z	NB	NM	NS	Z	PS	PM	PB
NS	NB	NM	NS	PS	PM	PB	PB
NM	NB	NM	NS	PM	PB	PB	PB
NB	NB	NM	Z	PM	PB	PB	PB

Table 2: Fuzzy Integral Rulebase

I\E	NB	NM	NS	Z	PS	PM	PB
I	NB	NM	NS	Z	PS	PM	PB

In a similar manner the fuzzy integral controller utilises the Integral Rulebase, as defined by Table 2.

The nature of the input windows ensures that several rules may be activated together, the output of each rule being modified by a weighting term. The output window contains seven asymmetrical sets [Fig.3] which due to previous work (Polkinghorne *et al*, 1992) is known to create a smoother output from the controller. By employing the centre of area method to all the active output sets, a deterministic controller output may be obtained.

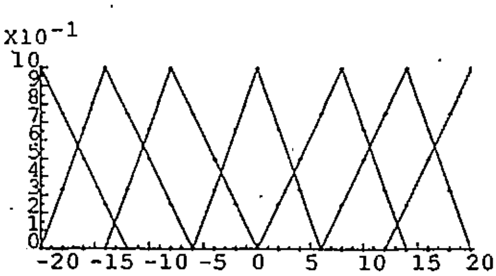

Fig. 3. Fuzzy Output Window

4.1 Course-Keeping Fuzzy Logic Autopilot

The window limits for yaw error and rate were adjusted to obtain an optimum value of RMS yaw error. The final window limits with the disturbance inputs of sea state 4 were yaw error ±10°, rate ±1.5°s^{-1} and rudder ±20°, [Fig.4]. The integral controller utilised the identical yaw input window with an output rudder window limit of ±12°.

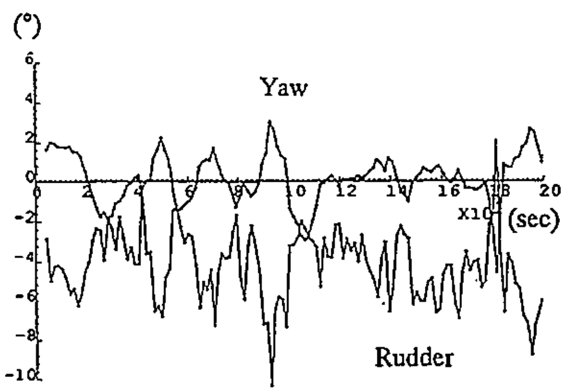

Fig. 4. Yaw & Rudder Responses (FUZZY PID) - Sea State 4

To test the robustness qualities of the fuzzy logic controller over a range of significant operating weather conditions, both the controllers were subjected, without change, to sea state variations. The results are summarised by Table 3.

For all tested conditions the fuzzy PID controller proved to be more successful at minimising the RMS yaw error.

Table 3: Comparison of Controllers to Sea State Alterations

RMS Yaw Error (°)	PID	Fuzzy PID
Sea State 3	0.34	0.15
Sea State 4	1.32	0.99
Sea State 5	5.96	5.17
RMS Rudder Action (°)	**PID**	**Fuzzy PID**
Sea State 3	1.82	1.82
Sea State 4	4.25	4.26
Sea State 5	11.59	11.42

5. CONCLUSIONS

The principles of fuzzy logic PID controller have been shown to successfully control the yaw response of a small vessel. In the course-keeping mode the fuzzy autopilot reduced the RMS yaw error with a slight rise in RMS rudder activity being noticeable. The output of the fuzzy controller is naturally noisy and could be improved by the addition of a filter which would reduce the RMS rudder action.

The general performance of the fuzzy logic PID controller has been shown to be superior to the PID autopilot over a range of operational conditions. Equally the fuzzy autopilot has demonstrated its robust qualities by operating with higher levels of performance when applied to alternative vessel models. A useful advancement would be the development of the controller into an intelligent version with the ability to achieve rulebase modifications on-line when applicable.

ACKNOWLEDGEMENTS

The authors would like to thank the Marine Technology Directorate (SERC), Marinex Industries Ltd and the University of Plymouth for support to undertake the investigation into "Modelling and Control of Small Vessels", (Grant Ref Number GR/G21162).

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THE IMPLEMENTATION OF A FUZZY LOGIC MARINE AUTOPILOT

M.N.Polkinghorne* G.N.Roberts** R.S.Burns*

*University of Plymouth, U.K.
**Royal Naval Engineering College, U.K.

ABSTRACT

In the field of ship control the Proportional plus Integral plus Derivative (PID) controllers remain common place. However, increasingly new autopilot strategies, promising higher levels of robustness and/or adaptive qualities, are being proposed as possible successors to the PID. Fuzzy Logic is a modern control technique which is currently finding an increasing and diverse range of novel applications. By means of full scale sea trials, a newly developed Fuzzy Logic autopilot is evaluated and a comparison made to its conventional equivalent.

1. INTRODUCTION

Marine vessels are non-linear time variant systems. therefore changes in speed, water depth or mass loading may cause a change in their dynamic characteristics. The severity of the weather will also alter the magnitude and direction of any disturbance effects caused by the wind, waves and current. The problem of autopilot control for such vessels is therefore inherently difficult. This is particularly so in the case of small craft whose sensitivity to incorrect control action is accentuated by their responsiveness to helm adjustments. Small vessels may be considered to be those of less than thirty meters in length and could be for commercial or leisure usage. Automatic control may be utilised for roll reduction van der Klugt (1), track-keeping Zuidweg (2), navigation Hashiguchi (3), automatic berthing Yamato *et al.* (4) or collision avoidance Koyama and Jin (5). However it is the autopilot application of course-keeping/course-changing where the proposed Fuzzy Logic controller is most useful. Due to the small draft of the considered type of ship, when the external environmental disturbances are applied to the hull, the low inertia present creates little resistance to the induced heading change. The autopilot performance must therefore be swift and decisive to counter any such effects by employing an opposing rudder condition.

It is therefore a necessity of a successful autopilot design that by its very nature, the obtainable level of performance must be either robust and relatively insensitive to the alterations in vessel dynamics and external disturbance factors, or alternatively, must be adjustable by the mariner on demand. In practice the latter has been proven to be unsuccessful due to a general inability of the mariner to fully understand the consequences of his/her actions when presented with a range of tuneable parameters. The resulting performance levels in such cases are normally still inadequate.

Poor controller performance may result in an oscillatory down-track course which increases distance and therefore trip time and fuel consumption. Wild and undesirable rudder movements may be produced which not only causes excessive wear to the rudder mechanism and induces drag, but also uses unnecessary power which is of particular importance when considering sail vessels whose power is often limited to a battery supply.

Modern control techniques of H∞ Fairbairn and Grimble (6), Optimality Burns (7), Self-Tuning (8), Model Reference van Amerongen (9), Neural Networks Endo *et al.* (10) and Fuzzy Logic van Amerogen (11) have all been applied to the field of large ships over recent years in an attempt to improve autopilot performance over the entire operating envelope. In the case of small vessels there has been little research of this kind. Previous studies by Polkinghorne *et al.* (12 & 13) have demonstrated the scope for Fuzzy Logic control in this area. The excepted robust qualities of the Fuzzy techniques and its ability to be advanced into an 'intelligent' form (the Self-Organising Controller or SOC) mean that detailed autopilot research into Fuzzy control of small vessels may well prove to be one of the most exciting and innovative areas of marine development currently being undertaken. The commercial exploitability of such a device could be vast given the huge number of craft currently utilising the PID alternative.

2. FIXED RULEBASE FUZZY LOGIC

Fixed Rulebase Fuzzy Logic (FRFL) has been developed as a means of coping with the decision process when only imprecise data is available to work with. If rigid mathematical relationships between

component parts of the process can be defined, then analysis, and subsequent decision making, may be undertaken with relative certainty of a successful conclusion. However, in the cases when such prior understanding is not possible, yet a realistic assessment of the decision outcome is required, the task is considerably more difficult to describe in quantitative terms. A technique is therefore required which is capable of utilising qualitative, linguistic or just generally imprecise, information. FRFL techniques currently employed in a wide range of applications appear to demonstrate this ability, and consequently are generating considerable interest, particularly in the field of control engineering. The concept of FRFL is derived from the principles of Fuzzy Set Theory as proposed by Zadeh (14). Given the possible advantages of using a Fuzzy Logic Controller (FLC) for autopilot applications, it is fully understandable that the complexities of the controller itself are far greater than would be associated with the conventional PID version. If the basic working philosophy of the FLC is to be investigated, then any inherent complexities must be minimised at the preliminary testing stage to allow fair comparisons to be carried out between autopilot types. Therefore it is the ability of the FLC to control, given equal information to the conventional PID autopilot, which requires initial investigation. Should these result prove favourable, then the arguments for extension to wider internal non-linearities and even adaptability hold true. To this aim a FLC is developed which will closely emulate the PID controller when subjected to similar environmental conditions, but will also retained the basic inherent Fuzzy advantages.

3. FUZZY LOGIC AUTOPILOT

The basic design of a standard form of FLC contains three elements, these are:

1. Fuzzification of inputs using Fuzzy windows.
2. Defuzzification of outputs using Fuzzy windows.
3. Rulebase relating Fuzzy inputs to Fuzzy outputs.

For this autopilot application a fourth component is required to compensate for any constant disturbance effects caused by wind, waves, or current, this being a Fuzzy Integral action.

3.1 Input Fuzzification

Fuzzification is the methodology by which the 'real world' deterministic inputs may be transformed into a Fuzzy format for utilisation within the FLC. Previous autopilot applications of Fuzzy Logic, Sutton [15], have restricted the inputs to those of heading error and rate of change of heading error, each variable being fuzzified individually by employing a Fuzzy window which contains a series of Fuzzy Sets.

The chosen Fuzzy Sets are deemed to represent the working envelope of the controller for a particular input variable. However, the shape, number and position of the sets is design dependant. Typical shapes include triangular, trapeziodal and gaussian sets. For the purpose of computational efficiency, the triangular shaped sets require the least amount of storage capacity and are comparatively easy to design since they operate about a clearly distinct set point. The set point can be defined as the point at which the function describing the set has a membership value of unity. For these reasons triangular Fuzzy Sets were used throughout the development of the FLC

As the number of utilised sets is raised, so the complexities of the FLC increase greatly. It is therefore of paramount importance that the set number is minimised for any application where computational storage and power is restricted by physical limits. Conversely, if the number of sets for each window is too low, then the range of permutations used to derive the controller outputs becomes restricted and only linear control possible. Following a heuristic design approach, it was found that the minimum number of sets which could successfully describe the inputs for a small vessel autopilot application was seven. However, the use of seven sets requires the central set point to be placed on the zero position in the universe of discourse. In practice the case when inputs are zero is not of paramount importance, and therefore to employ eight sets with an even distribution of four on either side of the zero mark, enables the defined set points to more fully describe the significant controller inputs. Symmetry of the given sets around the zero point enables the zero input condition to be represented by a blend of both positive and negative sets.

At the point when a particular set has a membership value of unity, it is important to ensure no overlap from adjacent Fuzzy Sets exists. At the set point the set may therefore be considered to fully describe the input, any activation of the surrounding sets in this situation reduces the importance and thus the effectiveness of any one individual set. The input window's universe of discourse was defined in its minimalistic form as twenty-one discrete intervals, at each interval the sets having a membership value in the range zero to unity. Each set is given a linguistic label to identify it, in the range Positive Big (PB), Positive Medium (PM), Positive Small (PS), Positive Tiny (PT), Negative Tiny (NT), Negative Small (NS), Negative Medium (NM) and Negative Big (NB). The identical window design was utilised for both inputs to conserve required memory storage in accordance with implementation hardware restrictions, only the window limits being varied in each case.

The set points should be placed in such a manner that they represent the positions where a change in controller action is required. As the Fuzzy Sets within the Window overlap, then a transition between differing control strategies may be enforced. The speed of this transition is dictated largely by the degree of overlap between Fuzzy Sets and the Fuzzy significance of the sets in question. In the case of input values which fall outside the extremities of the input windows, these values are saturated to the size of the window limits. It is therefore essential that the input windows cover the actual full range of useful inputs, as no new control configurations are possible for inputs which fall within the saturated regions. In order that no detrimental effects on the input resolution were caused by each input window, the most suitable window limits were determined to be ±15° for heading error and $\pm 5°s^{-1}$ for the rate of change of heading error.

Whilst in most cases the Fuzzy Input Sets are symmetrical about their set point, it is possible to design the sets in a non-symmetrical (non-linear) manner. This technique is particularly advantageous when a relatively large universe of discourse is required to provide a high accuracy of control about a point, e.g. zero point, whilst maintaining a minimum number of operational sets. In the small vessel autopilot application, there is a need for a high level of control during course-keeping, i.e. when the course error is within the range ±3°. This effect may be achieved by the utilisation of small angled Fuzzy Sets, thereby ensuring that several sets operate within the course-keeping performance envelope. In contrast, during the course-changing mode, the universe of discourse is required to represent a much wider range of heading errors. Therefore, large angled sets are required so that a much larger proportion of the window may be described by each set, thus ensuring that set numbers are to kept to a minimum [Figures 1 & 2].

In previous maritime studies the two modes of course-keeping and course-changing were either treated as separate modes of operation (15), or required the addition of a secondary level rulebase for 'close control' Farbrother (16). By employing non-symmetrical set shapes in the described manner, both effects can be successfully incorporated into the same input window.

3.2 Output Defuzzification

Defuzzification is the process by which a Fuzzy output value may be converted into the relevant deterministic value for use by the real world. The basic foundation of the Fuzzy output mechanism is an output window of similar form to that utilised for the controller inputs. The size of the window limits is restricted by the saturation limits of the control actuator. In this case, for full scale autopilot testing, the control actuator is the rudder, with physical movement limited to ±30°.

Given that the Fuzzy output window contains a series of Fuzzy Sets, and that the Fuzzy output will be described in the form of identified Fuzzy Sets with their associated membership values, then a means of defuzzification is required. It is possible to consider the output to be at the point with the maximum membership. When more than one peak is present then their positions may be averaged. This 'mean of the maixima' method has been compared as analogous to a multi-level relay Kickert (17), however the full concept of fuzziness as derived by the FLC is minimised by the selection of just maximum set memberships since lower membership elements of the output window become irrelevant. An alternative strategy is to apply the 'centre of area method' to the entire output window, considering the higher membership value where two active output sets overlap.

This technique is thought to provide a smoother output (16) due to the incorporation of the lesser fuzzy elements within the output window. Given the nature of the 'centre of area method' it is important to realise that the centre of a symmetrically shaped set will always be in the middle, irrespective of the membership value of that set. By employing non-symmetrical output sets this undesirable feature of defuzzification may be overcome. Using a similar approach to the design of the input windows, it was found that the minimum number of Fuzzy Sets required to successfully defuzzify the Fuzzy output was seven. Due to the non-linear shape of the sets, the number of discrete intervals required to fully describe the output window's universe of discourse was found to be twenty-one. Utilising the details of the output window, the 'centre of area method' for this application may be defined as:

$$\delta_d = \frac{\sum_{i=0}^{20} \delta_i \mu(\delta_i)}{\sum_{i=0}^{20} \mu(\delta_i)} \qquad (1)$$

where:

δ_d = Deterministic controller output.
δ_i = discrete interval in universe of discourse δ.
μ = Fuzzy membership at discrete interval δ_i.

When giving consideration to the incorporation of an integral action, the described form of output window was found to cause difficulties. Whilst it is possible to consider the integral action to be a third input with individual input window and rulebase (12), it is more advantageous to calculate the integral in terms of a shift to negative or positive of the established output from the two input FLC. In order for this phenominum to be possible, the conventional output window with only seven set points proved ineffective. A new output window was therefore designed which contained two hundred and one Fuzzy Singletons, i.e. Fuzzy Sets with only one element where the membership function has a magnitude greater than zero. Thus the number of output permutations becomes vastly increased, and the performance of the integral action significant.

3.3 Rulebase Derivation

The Fuzzy Rulebase is the heart of the FLC and contains the input/output relationships that form the control strategy. Therefore, a large proportion of the FLC's power is contained in this rulebase and determination of the correct magnitudes for each element is essential. For this autopilot application, it is understood that the final controller performance should be of a form similar to that obtained from the PID controller. The PID data was therefore analysed for each combination of input set points and an output singleton identified that would give an equivalent response, [Table 1].

TABLE 1. - Fuzzy Rulebase

Rate\Error	-4	-3	-2	-1	+1	+2	+3	+4
-4	-100	-71	-60	-53	-46	-40	-29	-15
-3	-65	-51	-40	-33	-26	-19	-9	5
-2	-50	-36	-35	-18	-11	-4	6	20
-1	-40	-26	-15	-8	-1	5	16	30
+1	-30	-16	-5	1	8	15	26	40
+2	-20	-6	4	11	18	25	36	50
+3	-5	9	19	26	33	40	51	65
+4	15	29	40	46	53	60	71	100

In practice, the FLC combines many such input values to obtain an overall Fuzzy output using the Max-Min method of inference.

5. AUTOPILOT TESTING

Both the FLC and PID controllers were tested in course-keeping modes, in a low sea state so that performance limitations were imposed strictly by the autopilots and not by the environmental conditions.

Small vessel tests were carried out over a 2.5 mile course at 18 knots, and with a desired heading of 50°. The resulting performance for both vessel heading and rudder responses are shown in Figures 3 to 6 for the FLC and PID controllers respectively.

6. CONCLUSIONS

During the sea trials, it became apparent that the FLC was operating in a highly successful manner. After consideration of the data obtained for these trials, it is clear that this impression was true. Given that it was the intention of this initial FLC design to mimic the performance of the conventional PID autopilot, similarity in the respective performances is to be expected, and indeed desired.

In the case of the vessel heading, the results demonstrated that both controllers were capable of maintaining the required course with a high degree of accuracy. The derived yaw responses are therefore of a similar order. However, when inspecting the actual size of the course deviations, it becomes clear that the PID autopilot wandered further from the desired course on many more occasions before correction, whilst the FLC performed in a superior and more consistent manner.

When considering the rudder response, the mean rudder activities for the respective controllers were almost identical. The maximum rudder movements were found to correspond to the respective vessel headings, therefore the FLC demonstrated far less rudder movement in comparison to the PID autopilot. For a comparable course, the FLC has therefore demonstrated a considerable saving in rudder movement. This effect will obviously prolong the life expectancy of the entire steering mechanism.

In conclusion it must be recognised that the FLC contains far more potential than has been exercised by this initial set of trials. The results discussed have identified that the FLC, when designed to emulate a PID controller, can maintain an equal standard of course-keeping whilst employing a smoother rudder action. Only by equating the two design methodologies in this manner can this important fact be demonstrated as being true. Given the establishment of the FLC performance capabilities, further extension is possible by manipulation of the rulebase and/or input windows so that the final FLC design can be expected to considerably outperform the PID autopilot.

7. ACKNOWLEDGEMENTS

The authors would like to thank the Marine Technology Directorate (SERC), Marinex Industries Ltd and the University of Plymouth for support to undertake the investigation into "Modelling and Control of Small Vessels", (Grant Ref. Number GR/G21162).

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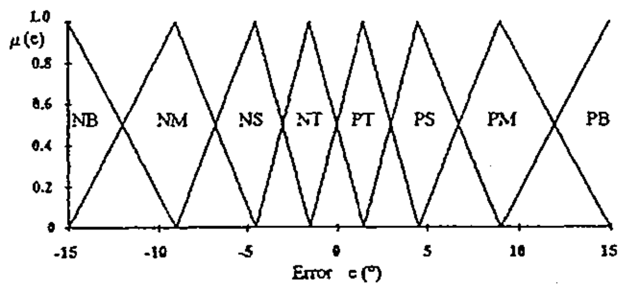

Figure 1. Non-Linear Fuzzy Logic Input Window for Heading Error

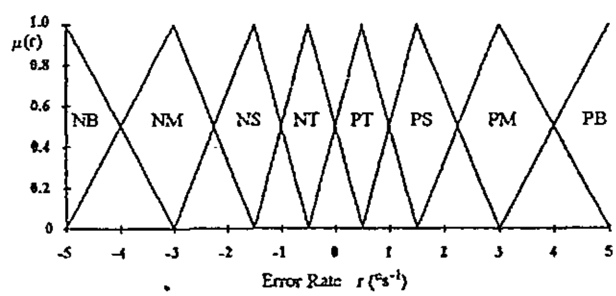

Figure 2. Non-Linear Fuzzy Logic Input Window for Rate of Change of Heading Error

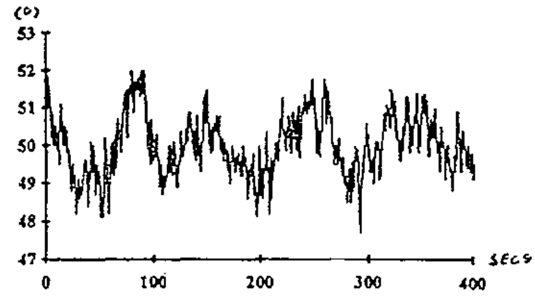

Figure 3. Vessel Yaw Response (FLC)

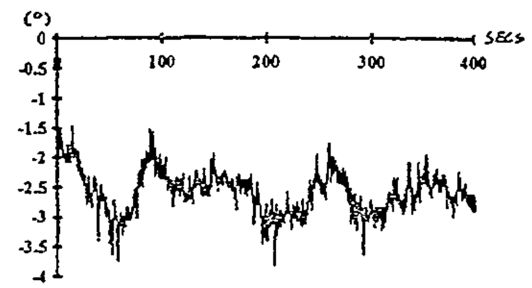

Figure 4. Vessel Rudder Response (FLC)

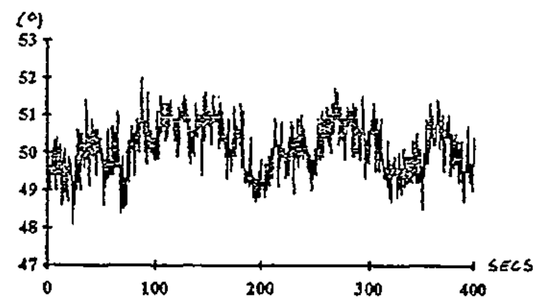

Figure 5. Vessel Yaw Response (PID)

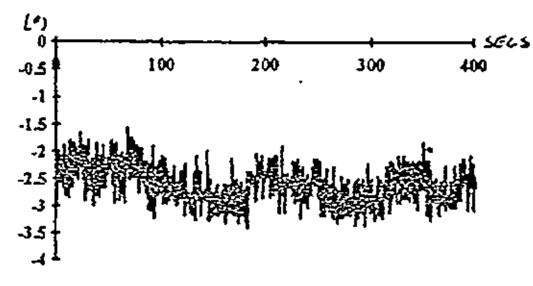

Figure 6. Vessel Rudder Response (PID)

THE IMPLEMENTATION OF FIXED RULEBASE FUZZY LOGIC TO THE CONTROL OF SMALL SURFACE SHIPS

M.N.Polkinghorne,* G.N.Roberts,** R.S.Burns* and D.Winwood***

*University of Plymouth, Drake Circus, Plymouth, U.K.
**Gwent College of Higher Education, Newport, U.K.
***Marinex Industries Ltd, Factory Rd, Upton, Poole, UK.

ABSTRACT. For ship control, the Proportional plus Integral plus Derivative (PID) controllers remain common-place. However, increasingly new autopilot strategies, promising higher levels of robustness and/or adaptive qualities, are being proposed as possible successors to the PID. Fuzzy logic is a modern control technique which is currently finding an increasing and diverse range of novel applications, both in its fixed-rulebase and intelligent forms. By means of full scale sea-trials, a newly developed fuzzy logic autopilot is evaluated for both course-keeping and course-changing, and a comparison made to its conventional equivalent.

Key Words. Fuzzy Control; Marine Systems; Ship Control; Autopilot; Small Vessel.

1. INTRODUCTION

Since marine vessels are non-linear, time-variant systems, any changes in speed, water depth or mass loading may cause a change in their dynamic characteristics. The severity of the weather will also alter the magnitude and direction of any disturbance effects caused by the wind, waves and current. The problem of autopilot control for such vessels is therefore inherently difficult. This is particularly so in the case of small craft whose sensitivity to incorrect control action is accentuated by their responsiveness to helm adjustments. Small vessels may be considered to be those of less than thirty meters in length and could be for commercial or leisure usage. Due to the small draft of the type of ship considered, when the external environmental disturbances are applied to the hull, the low inertia present creates little resistance to the induced heading change. The autopilot performance must therefore be swift and decisive to counter any such effects by employing an opposing rudder condition.

For any successful autopilot design, it is a necessity that the obtainable level of performance must be either robust and relatively insensitive to the alterations in vessel dynamics and external disturbance factors, or alternatively, must be adjustable by the mariner on demand. In practice the latter has been proven to be unsuccessful due to a general inability of mariners to fully understand the consequences of their actions when presented with a range of tuneable parameters. The resulting performance levels in such cases are normally still inadequate.

The result of poor controller performance may be an oscillatory down-track course which increases distance and therefore trip time and fuel consumption. Wild and undesirable rudder movements may be produced, which not only cause excessive wear to the rudder mechanism, but also use unnecessary power. The latter is of particular importance when considering sail vessels whose power is often limited to a battery supply.

In the field of large ships, various modern control techniques have been applied to large ships in an attempt to improve autopilot performance over the entire operating envelope: H^{∞} (Fairbairn and Grimble, 1990), Optimality (Burns, 1990), Self-Tuning (Mort, 1983), Model Reference (van Amerongen and Unink Ten- Cate, 1975), Neural Networks (Endo *et al.*, 1989) and Fuzzy Logic (van Amerongen *et al.*, 1977). In the case of small vessels there has been little research of this kind. Previous studies by the authors (Polkenhorne et al 1992, 1993) have demonstrated the scope for fuzzy logic control in this area. The accepted robust qualities of the fuzzy technique and its ability to be advanced into an "intelligent" form (the Self-Organising Controller or SOC) mean that detailed autopilot research into fuzzy control of small vessels may well prove to be one of the most exciting and innovative areas of marine development currently being undertaken. The commercial potential of such a device could be vast, given the huge number of craft currently utilising the PID alternative.

When only imprecise data is available to work with, Fixed Rulebase Fuzzy Logic (FRFL) has been developed as a means of coping with the decision process. If rigid mathematical relationships between component parts of the process can be defined, then analysis, and subsequent decision making, may be undertaken with relative certainty of a successful conclusion. However, in the cases when such prior understanding is not possible, yet a realistic assessment of the decision outcome is required, the task is considerably more difficult to describe in quantitative terms. A technique is therefore required which is capable of utilising qualitative, linguistic, or just generally imprecise, information. FRFL techniques currently employed in a wide range of applications appear to demonstrate this ability, and are consequently generating considerable interest, particularly in the field of control engineering. The concept of FRFL is derived from the principles of Fuzzy Set Theory (FST) as proposed by Zadeh (1965). An excellent review of fuzzy sets is given in the work of Sutton and Towill (1985), whilst several early applications are reviewed by Tong (1977).

2. STRUCTURE OF A FUZZY LOGIC AUTOPILOT

Classical and modern control theories have been utilised for many years to overcome control problems successfully, where the system is linear in nature and may be described mathematically. Many systems, e.g. ship dynamics, are non-linear and/or time-variant systems. Therefore, with these conventional approaches it is not always possible to design a controller that can fully cope with the system's requirements.

In many such cases the system was operated, prior to automation, by a human controller who would undertake manual adjustments in order that a successful and acceptable level of control was maintained. It is considered that the ability of human operators to cope with system non-linearities can be linked to their imprecise operating characteristics, i.e. inputs to the human operator often in the form of:

"a big output is required in response to a big input stimulation"

Given that the definition of "big" will most certainly be different for various applications, in each specific application the human operator will "feel" that one value may be big and another may not. Consequently, to put a precise value on the term "big" would destroy the imprecision and general vagueness of the human control strategy, thereby reducing the ability to cope with such a diverse range of situations and circumstances.

If control techniques fail where human instinct was successful, then there is a clear reason for pursuing a path towards an automatic controller with a more human-like reasoning mechanism. Such a device is the Fuzzy Logic Controller (FLC) which utilises imprecise fuzzy sets and relationships. The development of an FLC as the autopilot for a small vessel is therefore a very worthwhile venture. The basic design of a standard form of FLC contains three elements. These are:

1. Fuzzification of inputs using fuzzy windows.
2. Defuzzification of outputs using fuzzy windows.
3. Rulebase specification relating fuzzy inputs to fuzzy outputs.

3. INPUT FUZZIFICATION

The methodology by which deterministic inputs are transformed into a fuzzy format for utilisation within the FLC is called "fuzzification". Previous autopilot applications (Farbrother, 1990; Sutton, 1987) using fuzzy logic have restricted the inputs to those of heading error and rate of change of heading error, each variable being fuzzified individually by employing a fuzzy window containing a number of fuzzy sets. The chosen fuzzy sets are deemed to represent the working envelope of the controller for a particular input variable. However, the number and position of the sets is design-shape and application-dependent. Typical shapes include triangular, trapezoidal and gaussian sets. For the purpose of computational efficiency, the triangular-shaped sets require the least amount of storage capacity and are comparatively easy to design since they operate about a clearly distinct set point. The set point is defined as the point at which the function describing the set has a membership value of unity. From a performance perspective the triangular sets were found to generate a far smoother fuzzification over the given input range, than trapezoidal or gaussian-sets. For these reasons triangular fuzzy sets were used throughout the development of the FLC.

The complexities of the FLC increase greatly as the number of utilised sets is raised. It is therefore important that the set number is minimised for any application where computational storage and power is restricted by hardware limits. Conversely, if the number of sets for each window is too low, then the range of permutations used to derive the controller outputs becomes restricted and only linear control is possible.

Following a performance analysis, it was found that the minimum number of sets which could successfully describe the inputs for a small vessel autopilot application was seven. The use of seven sets requires the central set point to be placed about the zero position in the universe of discourse. However, in this application, the case when inputs are zero is not important enough to warrant a set which emcompasses zero, and therefore to employ eight sets with an even distribution of four on either side of zero, enables the defined set points to fully describe the significant controller inputs for both the course-keeping and course-changing modes. Symmetry of the given sets around zero enables the zero input condition to be represented by a blend of both positive and negative sets. At the point when a particular set has a membership value of unity, it is important to ensure no overlap from adjacent fuzzy sets exists. At the set point the set is therefore considered to fully describe the input, any activation of the surrounding sets in this situation reduces the importance and thus the effectiveness of the set with unity membership.

Whilst in most cases the fuzzy input sets are symmetrical about their set point, it is possible to design the sets in a non-symmetrical (non-linear) manner. This technique is particularly advantageous when a relatively large universe of discourse is required to provide a high accuracy of control about a particular operating point, e.g. zero, whilst maintaining a minimum number of operational sets. In the small vessel autopilot application, there is a need for a high level of control during course-keeping, i.e. when the course error is within the range ±3°. This effect may be achieved by the utilisation of small-angled fuzzy sets, thereby ensuring that several sets operate within the course-keeping performance envelope. In contrast, during the course-changing mode, the universe of discourse is required to represent a much wider range of heading errors. Therefore, large-angled sets are required so that a much larger proportion of the window may be described by each set, thus ensuring that set numbers are to kept to a minimum.

The input window's universe of discourse was defined in its minimalistic form as twenty-one discrete intervals, at each interval the sets having a membership value in the range zero to unity (Fig. 1). Each set was given a linguistic label to identify it, in the range Positive Big (PB), Positive Medium (PM), Positive Small (PS), Positive Tiny (PT), Negative Tiny (NT), Negative Small (NS), Negative Medium (NM) and Negative Big (NB). The identical window design was utilised for both inputs to conserve required memory storage in accordance with the hardware restrictions for implementation, only the window limits being varied in each case.

Set\μ(u_i)	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
NB	1.0	.75	.50	.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NM	0	.25	.50	.75	1.0	.67	.33	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NS	0	0	0	0	0	.33	.67	1.0	.50	0	0	0	0	0	0	0	0	0	0	0	0
NT	0	0	0	0	0	0	0	0	.50	1.0	.50	0	0	0	0	0	0	0	0	0	0
PT	0	0	0	0	0	0	0	0	0	0	.50	1.0	.50	0	0	0	0	0	0	0	0
PS	0	0	0	0	0	0	0	0	0	0	0	0	.50	1.0	.67	.33	0	0	0	0	0
PM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.33	.67	1.0	.75	.50	.25	0
PB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.25	.50	.75	1.0

Fig. 1 Non-Linear Fuzzy Input Window Definition

The set points should be placed in such a manner that they represent the positions where a change in controller action is required. As the fuzzy sets within the window overlap, then a transition between differing control strategies may be enforced. The speed of this transition is dictated largely by the degree of overlap between fuzzy sets and the fuzzy significance of the sets in question. In the case of input values which fall outside the extremities of the input windows, these values are saturated to the size of the window limits. It is therefore essential that the input windows cover the actual full range of useful inputs, as no new control configurations are possible for inputs which fall inside the saturated regions.

In previous maritime studies the two modes of course-keeping and course-changing were treated either as separate modes of operation (Sutton, 1987), or required the addition of a secondary level rulebase for "close control" (Farbrother, 1990). By employing non-symmetrical set shapes in the manner described above, both effects are successfully incorporated into the same input window. In order that no detrimental effects on the input resolution was caused by each input window, the most suitable window limits were determined to be ±15° for heading error (Fig. 2) and $\pm 5°s^{-1}$ for the rate of change of heading error (Fig. 3).

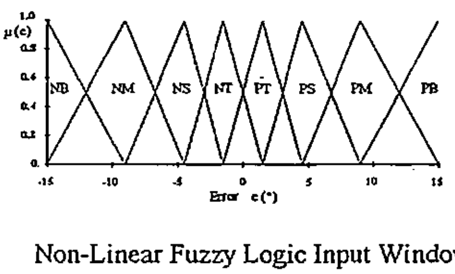

Fig 2. Non-Linear Fuzzy Logic Input Window for Heading Error

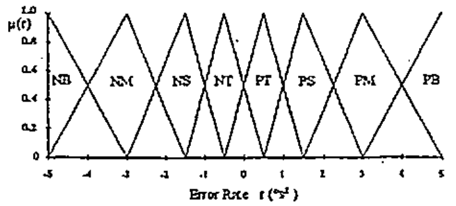

Fig 3. Non-Linear Fuzzy Logic Window for Rate of Change of Heading Error

After the input window for each of the input variables has been defined, the fuzzification mechanism may be initiated. The input variables are applied to their respective windows. Because only twenty-one discrete values describe each set across the entire universe of discourse, interpolation between points was employed to provide a higher fuzzy input resolution to the controller. The fuzzy sets contained within the input window may be linked together by a union (max) operation. Therefore, for any given input within the window, it becomes possible to evaluate which fuzzy set is "hit" with the maximum membership value. In many cases more than one set may be "hit", and in this instance the membership values should be considered in order of their significance.

Whilst it is possible to design an FLC which operates using only the single most maximum membership from each input window, it must be recognised that the imprecise ability of the control strategy would be severely impaired since the entire conceptual basis of the FLC is founded in both the applied grade of membership and the union of one or more fuzzy sets to describe an individual occurrence or event. By imposing the limitation of the single maximum membership, the fuzzified version of the deterministic value is confined to a single fuzzy set. The necessity for recognition of at least the two largest membership values is therefore established. However, should three or more such values be utilised, then the number of permutations for internal fuzzy relationships escalates rapidly. Whilst these less significant memberships are greater than zero, their magnitude is normally small. It is therefore ineffectual to include more than two maxima other than to increase FLC complexity.

By applying the given approach of fuzzification to the input window describing the input of error, it is possible to convert the deterministic input value into two fuzzy membership values with their associated fuzzy sets, where one membership is the maximum value for any set in the window for the point defined by the input, and the other is the next to maximum value. The two sets associated with these two membership values are therefore the fuzzy sets which best describe the given input. An identical approach was undertaken for the window describing the input of error rate, and this could be similarly applied for any other inputs.

The procedure of fuzzification is therefore complete for this autopilot application, with each input being fully described by the two fuzzy sets in each case with the maximum membership values.

4. OUTPUT DEFUZZIFICATION

The process by which a fuzzy output value may be converted into the relevant deterministic value is called "defuzzification". The basic foundation of the fuzzy output mechanism is an output window of a similar form to that utilised for the controller inputs. The size of the window limits is restricted by the saturation limits of the control actuator. In this case the control actuator is the rudder, with physical movement limited to ±30°.

Since the fuzzy output window contains a series of fuzzy sets, and the fuzzy output is described in the form of identified fuzzy sets with associated membership values, a means of defuzzification is required. It is possible to consider the output to be at the point with the maximum membership. When more than one peak is present then their positions may be averaged. This "mean of the maxima" method has been compared as analogous to a multi-level relay (Kickert, 1975). The full concept of fuzziness as derived by the FLC is minimised by the selection of just maximum set memberships since lower membership elements of the output window become irrelevant. An alternative strategy is therefore to apply the "centre of area method" to the entire output window, considering the higher membership value where two active output sets overlap.

Due to the incorporation of the lesser fuzzy elements within the output window, this technique is thought to provide a smoother output (Farbrother, 1990). Given the nature of the "centre of area method" it is important to realise that the centre of a symmetrically shaped set will always be in the middle, irrespective of the membership value of that set. By employing non-symmetrical output sets this undesirable feature of defuzzification may be overcome.

Using a similar approach to the design of the input windows, it was found that the minimum number of fuzzy sets required to successfully defuzzify the fuzzy output was seven. Due to the non-linear shape of the sets, the number of discrete intervals required to fully describe the output window's universe of discourse was found to be twenty-one, (Fig. 4). The final output window design is shown in Fig. 5:

Set\μ(u_i)	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
NB	1.0	.75	.50	.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NM	0	.33	.67	1.0	.75	.5	.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NS	0	0	0	0	.33	.67	1.0	.75	.50	.25	0	0	0	0	0	0	0	0	0	0	0
Z	0	0	0	0	0	0	0	0	.33	.67	1.0	.67	.33	0	0	0	0	0	0	0	0
PS	0	0	0	0	0	0	0	0	0	0	0	.25	.50	.75	1.0	.67	.33	0	0	0	0
PM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.25	.5	.75	1.0	.67	.33	0
PB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.25	.50	.75	1.0

Fig. 4 Non-Linear Fuzzy Output Window Definition

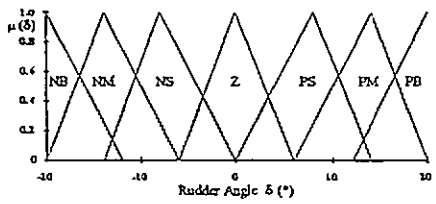

Fig. 5 Fuzzy Output Window

Utilising the details of the output window, the centre of area method for this application is defined as:

$$\delta_d = \frac{\sum_{i=0}^{20} \delta_i \mu(\delta_i)}{\sum_{i=0}^{20} \mu(\delta_i)} \qquad (1)$$

where:

δ_d = Deterministic controller output.
δ_i = Discrete interval in universe of discourse δ.
μ = Fuzzy membership at discrete interval δ_i.

5. FUZZY INTEGRAL ACTION

For this autopilot application an integral action is required to compensate for constant disturbance effects caused by wind, waves or current. When giving consideration to the incorporation of an integral action, the previously described form of output window was found to cause difficulties. Whilst it is possible to consider the integral action to be a third input with a corresponding individual input window, the resulting three-dimensional rulebase becomes computationally expensive. Separate rulebases may be considered (Kwok *et al*, 1991) which are linked either just before or after defuzzification (Polkinghorne *et al*, 1992); however, the additional computer code required for the extra fuzzification/defuzzification prevents this solution from being truly practical.

It is much more advantageous to calculate the integral in terms of a shift to negative or positive of the established output from the original two-input FLC, within the output window limits. In order for this phenomenon to be possible, the conventional output window with only seven fuzzy sets proved ineffective due to the coarse resolution of movement possible.

In order to facilitate integral action a new output window was therefore designed which contained two hundred and one fuzzy singletons, i.e. fuzzy sets with only one element where the membership function has a magnitude greater than zero. Although this may seem excessive, this number of fuzzy Singletons was determined as the minimum number required to provide a suitable integral resolution, without causing the controller to become either oversized computationally, or disjointed in its demanded control actuator movement.

Using this technique, the number of output permutations becomes vastly increased, and the rulebase must therefore be designed to reflect the full range of output sets. To aid this process the linguistic labels of the output sets were replaced with a numerical identifier in the range ±100. The output defuzzification (equation 2) for this novel form of window becomes:

$$\delta_d = \frac{\sum_{i=-100}^{100} \delta_i \mu(\delta_i)}{\sum_{i=-100}^{100} \mu(\delta_i)} \qquad (2)$$

6. RULEBASE DERIVATION

The heart of the FLC is called the fuzzy rulebase and contains the input/output relationships that form the control strategy. Therefore, a large proportion of the FLC's power is contained in this rulebase and determination of the correct magnitudes for each element is essential. By the variation of values within the rulebase, the operation of the FLC can be radically altered. At the initial stage of sea trials when it is imperative to establish the control effects generated by the differing control strategies, an attempt must be made to design the FLC in such a manner that it contains the same operational goals as the conventional PID autopilot. Only by this means may any significant findings in the resulting performances be attributed to the controllers themselves, and not to induced set-up differences.

The rulebase was therefore designed, following analysis of the PID controller, by allocating to each combination of input set points the corresponding PID output. It may therefore be assumed that the obtainable response from the FLC will be similar to that of the PID autopilot, with only inherent differences caused by the respective working methodologies being apparent. The conventional fuzzy rulebase is therefore modified to contain output sets which reflect the 201 fuzzy singlètons of the output window (Fig. 6).

Rate\Error	NB	NM	NS	NT	PT	PS	PM	PB
NB	-100	-71	-60	-53	-46	-40	-29	-15
NM	-65	-51	-40	-33	-26	-19	-9	5
NS	-50	-36	-35	-18	-11	-4	6	20
NT	-40	-26	-15	-8	-1	5	16	30
PT	-30	-16	-5	1	8	15	26	40
PS	-20	-6	4	11	18	25	36	50
PM	-5	9	19	26	33	40	51	65
PB	15	29	40	46	53	60	71	100

Fig 6. Non-Linear Fuzzy Rulebase

7. INFERENCE TECHNIQUES

No matter how extensive a rulebase becomes, it is unlikely that there will be a rule for every input variation. The declared rules are based on the assumption that the input sets are hit with a membership of unity. In practice, it is very often the case that the exact input set is not available and a nearest set is therefore 'hit' instead. When this feature of the FLC occurs, then the membership value of the hit set will be less than unity; therefore the declared fuzzy Conditional Statement is not completely true.

By use of an inference technique, it is still possible to utilise the given relationship, thus identifying the required output set; however, the inferred membership of the output set is based on the input memberships applied. By employing this technique, the FLC becomes capable of operating in regions not covered by the pre-selected input set points.

One such inference technique is called the max-min rule of inference (equation 3).

$$\mu_{\beta}(e)\times\mu_{Q}(r)\times\mu_{Z}(\delta)=\max[\min[\mu_{\beta}(e),\mu_{Q}(r),\mu_{R}(\delta)]] \qquad (3)$$

where:

$\mu_R(\delta)$ = Defined Fuzzy Conditional Statement between disparate universes of discourse error (e), rate (r) and rudder (δ).

Following this approach, it is possible to deduce the membership of the output set specified by the relationship R, given undefined input quantities for error and rate. This provides a pessimistic form of control (Kosko, 1992) which was found to induce low rudder activity in this autopilot application.

The relationship between the inputs and the defined rulebase is declared by the min operation to infer the output set's membership value. The output set "hit" is implied by the definition of the relationship. The union of the rules in the rulebase is then achieved by an overall max function. An alternative method of inference would be the max.max, or max product, technique. This method is thought to give an optimistic output and in practice was found to produce highly oscillatory rudder movements. Since the rulebase contains the fuzzy Conditional Statements between input set permutations, the membership of an identified output set is determined by a minimum operation.

8. AUTOPILOT TESTING

The FLC and PID controllers were both tested in course-keeping and course-changing modes. By utilising a relatively low sea-state, performance limitations were imposed strictly by the autopilots and not by the environmental conditions.

Small vessel tests were carried out over a 2.5 mile course at 18 knots, and with a desired heading of 50° to assess the course-keeping abilities of both controllers.

For course-changing, autopilot control may vary between large and small-scale demanded heading changes. The course-changing test therefore included step changes in desired heading of both 90° (large) and 30° (small). The resulting performance for both vessel heading and rudder responses, in the two modes of operation, are shown in Figs. 7 to 14 for the PID and FLC controllers respectively.

9. DISCUSSION AND AUTOPILOT EVALUATION

When considering the course-keeping results, it is clear that both controllers maintained the ship heading within an acceptable deviation from the desired course, i.e. approximately ±2°. To attain this level of performance, the PID utilises a high-frequency rudder action. Consequently the ship heading contains high-frequency elements. In contrast the FLC rudder action is much smoother, with the high-frequency elements being largely eliminated from both the rudder and heading responses. As a result, the FLC tends to induce slightly increased amplitude on the low-frequency components. The FLC can therefore be assumed to incur reduced rudder wear, power usage, fuel consumption and trip time when used as a replacement for the conventional PID autopilot.

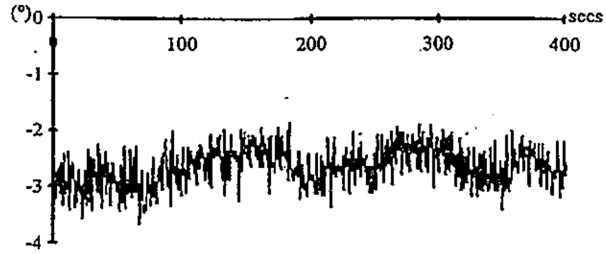

Fig 7. Rudder Response: Course-Keeping (PID)

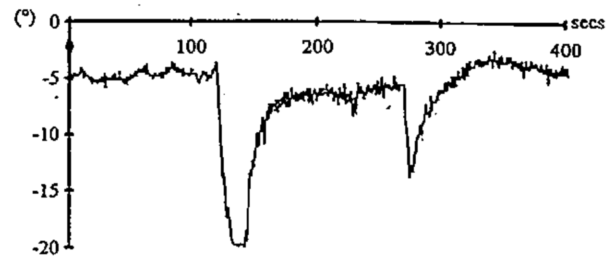

Fig 11. Rudder Response: Course-Changing (PID)

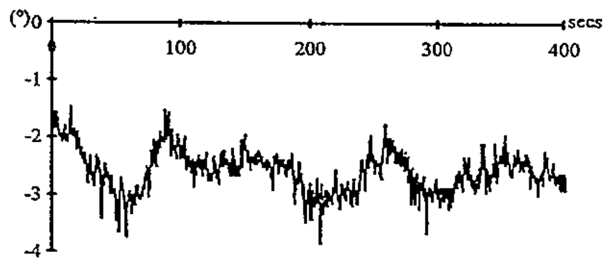

Fig 8. Rudder Response: Course-Keeping (FLC)

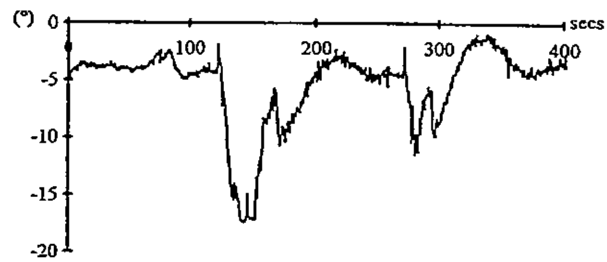

Fig 12. Rudder response:Course-Changing (FLC)

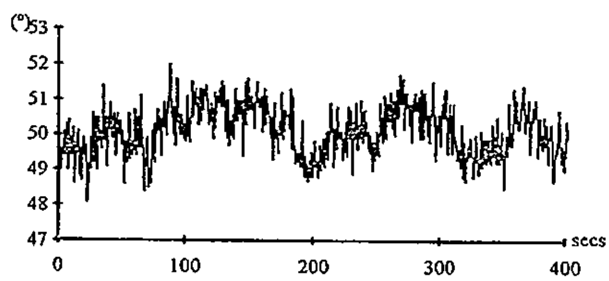

Fig 9. Yaw Response: Course-Keeping (PID)

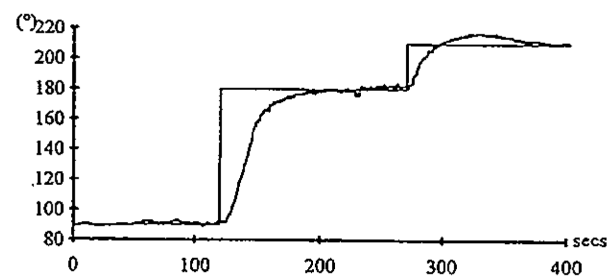

Fig 13. Yaw Response: Course-Changing (PID)

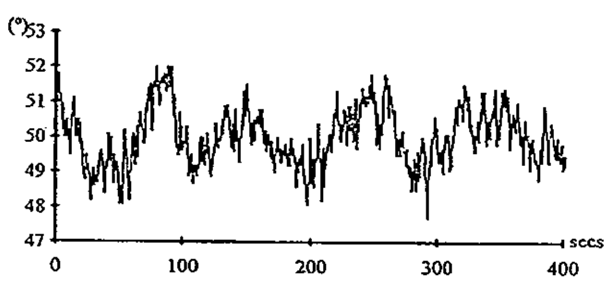

Fig 10. Yaw Response: Course-Keeping (FLC)

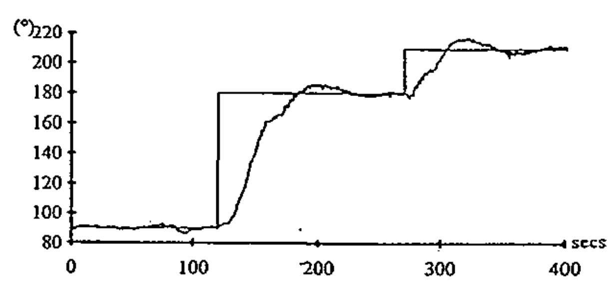

Fig 14. Yaw Response: Course-Changing (FLC)

When operating in course-changing mode, both controllers are seen to perform with similar rise times. However, the FLC provides a 30% reduction in settling time for the 30° heading change, and a 35% reduction for the 90° heading change. This improvement is effected at the cost of inducing a small, but acceptable, overshoot. Whilst it would appear that the PID response contains a lower level of damping, since both controllers were effecting nearly identical input/output relationships, this effect must be due to the control stratgies employed.

A qualitative assessment of the performances obtained for both autopilots indicates that the FLC portrays many desirable features. As both the PID and FLC autopilots were designed to produce identical desired rudder demands for the same inputs, the results presented clearly indicate the inherent differences between the two controller strategies. By refining the rulebase, a non-linear set of input/output relationships may be defined which would further enhance the control action obtained. Similarly, scope for intelligent operation via on-line rulebase adaptation (the Self-Organising Controller or SOC) would increase the operating envelope of the controller.

10. ACKNOWLEDGEMENTS

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