AN ADAPTIVE CONTROL FOR A CRAWLING UNMANNED VEHICLE BY USING PID CONTROL & NEURO-FUZZY LOGIC

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Abstract

This paper describes a new methodology to design an adaptive feedback controller for an unmanned crawling vehicle (UCV) having track style wheels. The motion of the vehicle is constrained by environmental uncertainties, which are represented by unknown friction coefficients between the tracks and ground surface. The controller, a combination of conventional Proportional-Integral-Derivative (PID) and Adaptive Neural Network Fuzzy Logic (ANNFL), is designed by using multi-objective optimization techniques from which the fixed control gains of PID controller and the adjustable control gains of ANNFL are obtained.

Using the nonlinear motion equations of the vehicle dynamics, the PID controller is designed at a nominal operating point and establishes a desired system response pattern of feedback (closed loop) control..

The ANNFL deals with the uncertainties to compensate the PID controller for reducing the "command following error" by tuning an additional gain feedback from the system output besides the fixed gain of the PID controller. ANNFL provides an adaptability and robustness for the integrated control strategy of the PID and ANNFL.

An example simulation is included to demonstrate the improved performance of this integrated control strategy in comparison with PID-only control.

1. Introduction

The unmanned crawling vehicle (UCV) having track style wheels is used for performing reconnaissance missions in the very shallow water (VSW) and surf zone (SZ). SZ can be referred to as the underwater range between 0 and 10 feet in depth, VSW is between 10 and 40 feet. The UCV also can be applied to explore and map the sea bottom at low cost. Furthermore, it can replace divers by performing a variety of hazardous missions in the coastal waters. Unlike typical driven vehicles, UCV's are deployed on a mission field in which the knowledge of the environment is unknown.

There are many uncertainties and nonlinearities affecting the vehicle's movement, and the adaptive controller must be designed to cope with these situations. In this paper, a new methodology is described to design an adaptive controller using conventional PID and ANNFL through the process of the computer aided design with multi-objective optimization [1].

The conventional PID-type controller is the most widely controller used in the industry due to its simple control structure, ease of design, and inexpensive cost. However, the PID-type controller cannot yield a good control performance if the controlled object is highly nonlinear and uncertain.

Another type of controller based on fuzzy logic[2] is being increasingly applied to many systems with nonlinearity and uncertainty [3]. The most successful fuzzy logic controllers applied to industrial plants are designed by control engineers. Unfortunately, defining membership functions of linguistic variables and formulating fuzzy rules by manual operation is time consuming work[4]-[7].

Additionally, few stability analyses for real fuzzy logic controllers are reported, so many people worry about their reliability.

The approach for this study is to answer these questions by proposing an integrated Nero-fuzzy logic PID controller. The PID controller is designed at a nominal operating point and establishes a desired system response pattern of feedback (closed loop) control. The ANNFL deals with the system uncertainties to compensate the PID controller by reducing the "command following error". This error is reduced by tuning an additional gain feedback from the system output besides the fixed gain of the PID controller. The ANNFL provides an adaptability and robustness for the integrated control strategy of the PID and ANNFL controller and makes it possible to control a system in real time. ANNFL is a functional relationship formulated in terms of the gain domain which is obtained through an optimization process to get the desired system response for the given possible known uncertainties within the bounded domains. The optimization technique (used to obtain not only the adjustable gains of ANNFL but also the gains of the PID Controller) is the multi-objective optimization using a Sequential Quadratic Program (SQP) method.

Another aspect of this study is to support the future development of an optimal control strategy for a group of crawling unmanned vehicles. Control characteristics having a smooth, stable tracking capability for each vehicle will allow the vehicle group to increase the search efficiency by reducing any discontinuities (gaps) in the searched area.

Recently, fuzzy logic and conventional techniques were combined to design fuzzy logic controllers, such as [8]-[16]. Some of the important research results are addressed in [11] and [12].

This paper is organized as follows: In section 2, the equations of motion are described for the crawling vehicle used in the simulation and in the developing controller. In sections 3 and 4, the multi-objective optimization method and the adaptive neuro-fuzzy inference system are described. In section 5, the proposed adaptive controller methodology is discussed. In the section 6, results of an example simulation are presented by comparing the integrated controller with a PID-only controller.

2. Equations of Motion for the Unmanned Crawling Vehicle

The equations of motion (for the crawling vehicle having track type wheel) used for the design of an adaptive controller is expressed under the assumption that there are the three degrees-of-freedom in a body-fixed coordinate system (x,y,φ). The x and y are a linear displacements at a body-fixed coordinate system which is aligned with the center of mass of the body and φ is an angular displacement around the z-axis. It also has the three damping coefficients (Kx, Ky, $K\varphi$) and the three friction coefficients (μx, μy, μ_φ). Kx, Ky and $K\varphi$ are proportional to the velocities of the vehicle (u,v *and* w_z) and are chosen by comparing the response of an open loop simulation with testing of a real vehicle. The μx, μy and μ_φ are the friction coefficients between the track and ground surface. We assume that the values of these coefficients are unknown but the upper and lower bounds are known because they are determined by the maximum driving force of the vehicle. In the model of the uncertainties, all possible factors such as the geometry of mission field and bottom conditions are represented in terms of the variation of these coefficients.

The vehicle motion is constrained by the normal force (mg) acting through the z-axis due to gravity (g) and the moment of inertia (Iz) around it. The buoyancy force (B_y) acts through the mass center in the opposite direction of the normal force so that the vehicle weight is W = (mg- B_y). The dimensions of the vehicle used in simulation and in the design of the controller are W = 100 lb, length (L) = 2.3 ft, Width (B) = 2 ft and height = 1 ft. The physical control inputs (D1,D2) are the driving forces supplied to both tracks through their traction motors. The linear motion in the x-direction of body is determined by the sum of D1 and D2, and the heading is controlled by the difference of D2 and D1. The simplified equations of motion are then given as follows

$$\mathbf{m}(du/dt - w_z v) = (D1+D2) - Kx\ u \sin(u) - \mu x(mg - B_y)\sin(u) \tag{1}$$

$$\mathbf{m}(dv/dt + w_z u) = - Ky\ v \sin(v) - \mu y\,(mg - B_y)\sin(v) \tag{2}$$

$$\boldsymbol{Iz}\ dw_z/dt = B/2\ (D2-D1) - K\varphi\ w_z\ \mathrm{sign}(w_z) - \mu_\varphi\, mgL\sin(w_z)/4 \tag{3}$$

The state variables are x, y, φ, u, v, w_z and the uncertainties are μx, μy and μ_φ.

3. Multi-objective Optimization

In order to obtain not only the adjustable gains of the ANNFL but also the gains of the PID controller for our proposed adaptive control strategy, the multi-objective optimization technique is used. Thanks to the well developed tool box of nonlinear control design (NCD) blockset in the Matlab program, the tunable parameters (which are the gains in the adaptive controller) are obtained through a process of optimization with the uncertainties taken from a bounded domain. The optimization algorithm which transforms the controlled system outputs into the constraints defined by the NCD blockset have the form:

$$\textbf{minimize}\ \alpha$$
$$X \in \mathbb{R},\ \alpha \in \boldsymbol{\Omega}$$

Such that $\quad \mathbf{G}(\boldsymbol{X}) - \boldsymbol{W} \cdot \alpha \le 0,$

$$\boldsymbol{X}_{\mathbf{l}} \le \boldsymbol{X} \le \boldsymbol{X}\mathbf{u}$$

where **X** is the vector of design parameters($X \in \mathbb{R}$) between lower bound and upper bound, ***W*** is weighting coefficients by which the relative degree of under- or over-achievement of a goal, $\mathbf{G}(\boldsymbol{X})$ is the vector of objective function and the vector, $(\mathbf{G}(\boldsymbol{X}) - \boldsymbol{W} \cdot \alpha)$ is the constraint error. The term $\boldsymbol{W}\,\alpha$ introduces an element of slackness into the system problem.

The implementation of the SQP method attempts to satisfy the Kuhn-Tucker equation, which is a necessary condition for optimality of a constrained optimization problem. The principal idea of the SQP algorithm is to form a Quadratic Programming (QP) problem at each iteration based on the quadratic estimate of the Hessian of the Lagrangian function. The line search is performed using a merit function. The routine uses an active set strategy for solving the QP subproblem. The two phases involved in the QP solution are:

1) Calculation of a feasible point.
2) Generation of an iterative sequence of feasible points, which converge to the solution.

In this method, an active set of constraints is maintained at the solution points. The solution to the QP produces a direction vector $\mathbf{D_k}$, which is used to form a new iterate

$$\boldsymbol{X}_{\mathbf{k+1}} = \boldsymbol{X}_{\mathbf{k}} + \boldsymbol{\delta}_{\mathbf{k}}\,\mathbf{D_k} \qquad (5)$$

The step length $\boldsymbol{\delta}_{\mathbf{k}}$ is determined to produce a sufficient decrease in a merit function. The merit function used by Han[16] and Powell[17] of the form below has been used in this implementation.

$$\mathrm{M}(x) = F(x) + \sum_{i=1}^{mk} R_i\, G_i(x) + \sum_{i=mk+1}^{m} R_i \max\{0, G_i(x)\} \qquad (6)$$

The penalty parameter was set by Powell

$$R_i = (R_{k+1})_i = \max\{\lambda_i, 1/2((R_k)_i + \lambda_i)\}, \quad i = 1,\ldots,m \qquad (7)$$

This allows positive contribution from constraints that are inactive in the QP solution but were recently active. In this implementation, the penalty parameter R_i is initially set to

$$R_i = \frac{\| \nabla F(x) \|}{\| \nabla Gi(x) \|} \qquad (8)$$

where $\| \ldots \|$ represents the Euclidean norm. This ensures larger contributions to the penalty parameter from constraints with smaller gradients, which would be the case for active constraints at the solution points.

4. Adaptive Network Based Fuzzy Inference System (ANFIS)

Conventionally, the mathematical tool (e.g., differential equations) is well suited for modeling a system that is well-defined and linear. But for the ill-defined, nonlinear system and a model characterized by the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses, a fuzzy inference system or fuzzy modeling has been employed by using fuzzy if-then rules. In the practical applications of fuzzy inference system, it is necessary to transform human

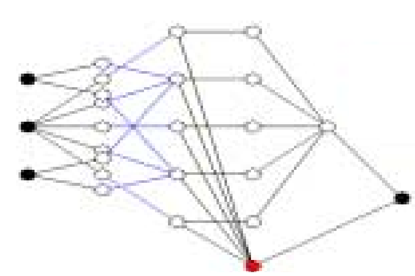

Figure 1. The Structure of ANFIS

knowledge or experience into the rule base and database of a fuzzy inference system and an effective method for tuning the membership function so as to minimize the output error measure or maximize performance index. In this respect, ANFIS has been developed and is well described in [18]. The adaptive controller in our proposed methodology requires the property of the ANFIS in order to construct a mapping functional relationship between an adjustable gain and reference and initial state variables.

We will now describe the architecture and the learning algorithm of ANFIS used in our proposed adaptive control strategy. Basically, ANFIS can be viewed as a kind of neural network with a supervised learning capability except it has more layers in its structure. As can be seen in Figure 1, it consists of five layers and each layer can be explained by comparison with a conventional fuzzy inference system and its reasoning process.

For simplicity in description, suppose that the fuzzy inference system under consideration has three inputs (x_1,x_2,x_3), one output (z), and five if-then rules of Takagi and Sugeno's type. One rule takes the following form:

Rule i : if x_1 is Ai and x_2 is Bj and x_3 is Ck, then $f_i = p_i x_1 + q_j x_2 + r_k x_3 + k$

where Ai, Bj, and Ck are the linguistic labels of each fuzzy sets and $\{p_i, q_j, r_k, k\}$ is the parameter set. The node functions in the same layer are of the same function family as below:

1) *Layer1* : Each node i in layer1 has a node function which is the membership function of Ai, Bj and Ck and it specifies the degree to which the given x_1,x_2,x_3 satisfies the quantifier Ai, Bj and Ck. In our application, the membership function is Gaussian in shape with a maximum equal to 1 and a minimum equal to 0, such as

$$\mu A_i(x_1) = \exp\{-((x_1-c_i) / a_i)^2 \} \quad (9)$$

and the output of Layer1 becomes

$$O_i^1 = \mu A_i(x_1) \quad (10)$$

Where $\{a_i, c_i\}$ is the parameter set in which parameters are referred to as premise parameters.

2) *Layer2* : Each node output represents the firing strength of a fuzzy rule. As the node function in this layer2, the generalized AND (T-norm operator) is used.

The output of Layer2 is, for instance,

$$Wi = \mu A_i(x_1) \text{ X } \mu B_i(x_2) \text{ X } \mu C_i(x_2) \quad (11)$$

3) *Layer3* : In this layer3, the *i*th node calculates the ratio of the *i*th rule's firing strength and the sum of all rules' firing strengths. This ratio is the normalized firing strength:

$$\overline{wi} = \frac{wi}{w1 + w2 + w3} \quad (12)$$

4) *Layer4* : Every node *i* in this layer is a node function

$$O_i^4 = \overline{wi} f_i = \overline{wi} \; (p_i x_1 + q_j x_2 + r_k x_3 + k) \quad (13)$$

Where $\{p_i, q_j, r_k, k\}$ will be referred to as consequent parameters.

5) *Layer5* : The single node in this layer computes the overall output as the summation of all incoming inputs:

$$O_i^5 = \sum_i \overline{wi} \; fi$$

$$= \frac{\sum_i \overline{wi} fi}{\sum_i \overline{wi}} \quad (14)$$

Thus we can construct an adaptive fuzzy inference system. The learning process updates the parameters associated with the membership function. This is accomplished with a backpropagation algorithm using gradient descent alone or a hybrid learning method combined with a backpropagation algorithm using least squares estimation.

5. Methodology to Design an Adaptive Controller for The Crawler Vehicle

Conventionally, the reason for using a PID-type controller in industrial application lies in its simple structure which can be designed by adjusting three controller parameters: K_p, K_i, and K_d.

$$\mathbf{U_{PID}} = K_{\mathbf{p}}\, e(t) + K_{\mathbf{d}}\, de(t) / dt + K_{\mathbf{i}} \int e(t)\, dt \quad (15)$$

In addition, the analysis method of its performance is well established for linear control systems. Utilizing the advantages of the PID type control, we propose a hybrid control scheme shown in Figure 2.

This hybrid controller is built by adding an Adaptive Neural Network-FuzzyLogic Controller (ANNFLC) into the PID controller. The PID controller is designed at a nominal operating point and establishes a desired system response pattern of feedback (closed loop) control. The ANNFLC deals with the uncertainties to compensate the PID controller for reducing the "command following error" by taking an additional gain feedback from the system output besides the fixed gain of the PID controller.

The ANNFLC provides an adaptability and robustness for the integrated control strategy of the PID and ANNFLC, and makes it possible to control a system in real time which cannot be found in only neural network control (NNC) having a self-adjustability. Instead of the self-adjusting mode of NNC at real time, in our proposed control strategy, the gains are formulated by a ANNFLC transfer function mode in advance at the design stage.

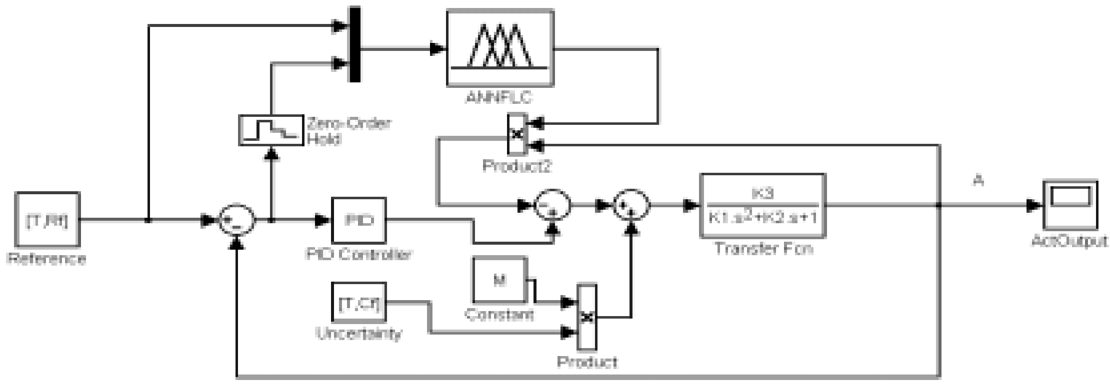

Figure 2. The Scheme of Hybrid Controller of PID and ANNFLC

The functional relationship of the ANNFLC in this scheme can be represented with the following expression. In general, a nonlinear system has the form

$$dx(t)/dt = f(x(t), u(t), w(t)) \quad (16)$$
$$y(t) = h(x(t)), \quad (17)$$
$$e(t) = y_d(t) - y(t) \quad (18)$$

where x(t), u(t) denote to state vector, control input, w denotes the uncertainty with known upper bound $w_{ub} >= \| w(t) \|$, y(t), e(t), $y_d(t)$, denote system output, system error and control reference, respectively.

When the system is equilibrated by the PID controller, the output of a control system having the ANNFLC has the form

$$y = f_1(y_d, \mathbf{K}, w) \quad (19)$$

The output of ANNFLC, $\boldsymbol{K}$, is a function of y_d and w. The perturbations, Δy, ΔK of y and $\boldsymbol{K}$ due to the perturbations of y_d and w are obtained by taking the first order terms in Taylor series expansion.

$$\boldsymbol{K} = f_2(y_d, w) \quad (20)$$
$$\Delta y = (\partial f_1 / \partial y_d) \Delta y_d + (\partial f_1 / \partial K) \Delta K + (\partial f_1 / \partial w) \Delta w$$
$$= c_1 \Delta y_d + c_2 \Delta K + c_3 \Delta w \quad (21)$$
$$\Delta K = (\partial f_2 / \partial y_d) \Delta y_d + (\partial f_2 / \partial w)$$
$$= c_4 \Delta y_d + c_5 \Delta w \quad (22)$$

By substituting (22) into (21), we can get Δy as

$$\Delta y = C_1 \Delta y_d + C_2 \Delta w, \quad (23)$$

When Δy_d is known, the system error Δy is linear to Δw.

$$\Delta y = C_2 \Delta w \quad (24)$$

Therefore, the amount of additional gain value in the ANNFLC depends upon the reference value, Δy_d and a system error, Δy. Both components become the inputs of the ANNFLS:

$$\boldsymbol{\Delta K} = c_4 \Delta y_d + c_6 \Delta y \quad (25)$$

where c4 and c6 are obtained by the process of multi-objective optimization techniques described in section 3. The application of multi-objective optimization to get control gains in a plant model with linear differential equation are in [1].

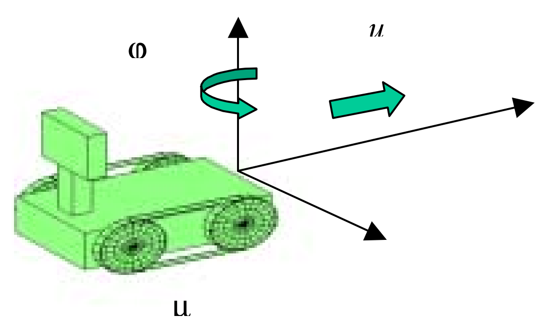

Figure 3. Crawling Vehicle with Track Type Wheel

In the design of a hybrid adaptive controller for a crawling vehicle having track style wheels, the controlled system outputs are heading, φ and a linear moving velocity, u of the vehicle (Figure 3). The variables φ and u, which are controlled by two traction motors, are determined by the output of the two PID controllers and the ANNFLC. The structure of the proposed ANNFLC is shown in Figure 4.

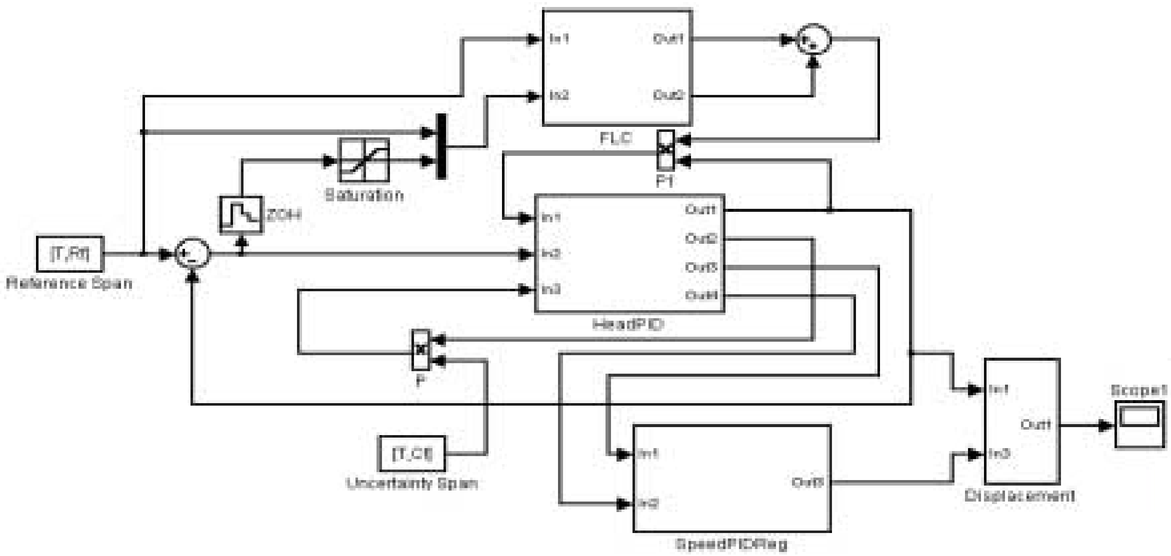

Figure 4. The Structure of the Proposed Adaptive Controller

φ(rad) \ μ	0.1	0.3	0.5	0.7	0.9	1.1	1.3	1.5	1.8
0.3	88.65	245.71	425.15	571.84	746.68	904.64	1069.9	1221.1	1461.8
0.5	58.93	167.35	246.66	343.02	455.21	540.91	637.72	742.86	885.51
0.8	41.65	99.47	159.53	217.09	276.80	337.05	397.74	470.52	602.05
1.0	35.90	82.05	128.64	175.64	223.04	270.81	318.92	367.35	440.43
1.2	32.06	70.46	109.16	148.16	187.45	227.00	266.81	306.86	367.35
1.5	27.66	57.36	87.23	117.29	147.51	177.90	208.46	239.17	285.51

Table 1 Additional Control Gains Used in ANNFLC of UCV

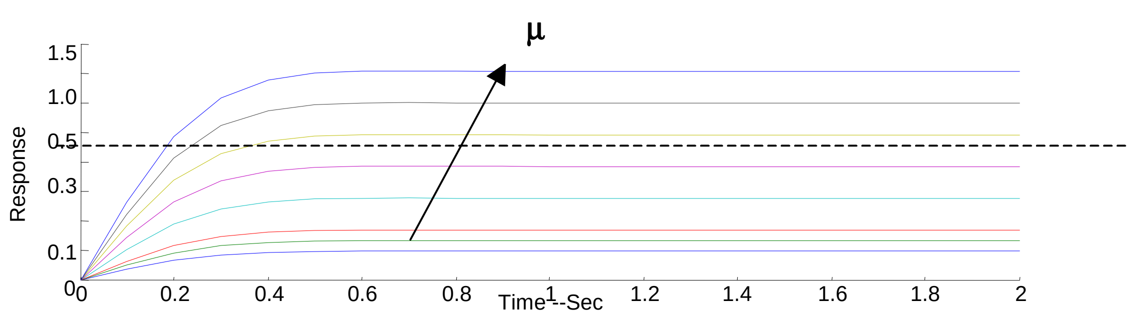

Figure 5. The Heading Responses According to Increasing μ at a Fixed Reference

The controller consists of a regulator and servomechanism. A PID controller for u belongs to the regulator type to keep a constant velocity. A PID controller and ANNFLC for φ belongs to the servomechanism type to track a desired heading. As an uncertainty, the friction coefficient μ acting between the track and ground surface is used.

We assume that μ is determined by any environmental conditions such as a surface roughness, geometry, and a hydrodynamic force (which are unknown). Even if the exact value of μ during vehicle operation is uncertain, it's approximation is measured by the difference of system output, $\Delta\varphi$ between an actual heading, φ_a and the φ_s obtained by using a standard friction (μ_s = 0.9). At that time, the PID controller is aimed to get a desired heading φ_d.

. We also assume that the possible range of μ is known between 0 and 2.0 according to [19]. An estimate for $\Delta\mu$ can be made by using a $\Delta\varphi$ at a given desired head φ_d and a measurement of $\varphi_{a.}$ In order to compensate $\Delta\varphi$ for $\Delta\mu$, it is necessary to design an additional control gain ΔK. This functional relationship is formulated by the ANNFLC through the multi-objective optimization process and then ΔK is a function of φ_d and $\Delta\varphi$. In the selection of the gains used in the two PID controllers and ANNFLC, we use the NCD block set in the toolbox of MATLAB.

The PID controller for the purpose of keeping a constant *u* is designed by using the motion equations described in section 2. The desired speed is 1.5 ft /sec, the coefficients, KpS, KiS, and KdS in the PID controller are KpS =1000, KiS =100, and KdS=0. The damping coefficients, *Kx, Ky* and $K\varphi$ are 50, 60 and 70 which are chosen by a simulation test of the plant model to get a similar response of the real vehicle at the same applied force. The coefficients used in the heading PID Controller are KpH = 2135.1, KiH = 0 and KdH = 654.72 which are selected to get a desired heading 1.0 rad at a constant velocity 1.5 ft/sec.

Both of the references used as the desired amounts are step functions. The actual system responses obtained by PID controllers take the pattern with stable, no overshoot and an enough tolerance within a settling time to follow the references.

The goal of the ANNFLS lies in keeping this ideal system response at all times for any uncertainty adaptively. At first, in the design of the ANNFLC having the functional relationship of the additional control gains with respect to φ_d and $\Delta\varphi$, we obtain the additional control gain table through multi objective process as can be seen in Table 1. Each gain is the value required to get the desired heading (the dash line in Figure 5) disturbed by the different values of μ, which are increased from the lower bound to the upper bound with a finite increment as in Figure 5.

The desired headings are in a possible operating range between 0^o and 90^o, which also are increased with a finite increment. The operating heading range can be extended between -90^o and 90^o by using the symmetric characteristic of heading behavior. And then we establish a relationship in equation (24) from Table 1 by taking a standard friction (μ_s) 0.9 . Using the standard friction value, the linear functional relation between the incremental ΔK and a heading incremental amount is obtained. The relation in equation (25) which is the output of ANNFLC is created by adding this relation to that of equation (24).

Therefore, the output of ANNFLC consists of two sub-problems. One is drawn from a state variable, a heading reference, and the other is derived from a heading reference and its heading error rate obtained from an uncertainty The ANNFLC in our application is the type of Sugeno fuzzy inference which map the input domains described above into an additional control gain. It is built on the following internal parameter, structure, and the training procedure, which has been used in the ANFIS program of MATLAB.:

A. The inputs are fuzzified by the membership functions (Gaussian Shape) which determine the degree to which they belong to each of the appropriate fuzzy sets as seen in Figure 6. We have three input variables so that there are three fuzzy sets which are the antecedents of the fuzzy rules.

Two of them are for uncertainty FLC in which one fuzzy set of heading reference is {NL1, NM1, NS1 ,PS1, PM1, PL1}and another sets for Error heading rate is {NL2, NM2, NS2 ,PS2, PM2, PL2}. One of them is for Reference FLC in which the fuzzy set is {NL3, NM3, NS3, ZR3, PS3, PM3, PL3}, where N,P,S,M,L and ZR are short for Negative, Positive, Small, Medium, Large, and Zero respectively.

B. The fuzzy operator (OR method) is applied to obtain one number that represents the result of the antecedent for fuzzy rules. The consequents of fuzzy rules are {SM,MS,M,SL,ML,L} in uncertainty FLC and {Lw, LwS, MS, M, SM, MM,L} in Reference FLC. Both fuzzy sets are linear type membership function described in section 4 as $f_i = p_i x_1 + q_j x_2 + k$. The coefficient sets $[p_i \;\; q_i \;\; k_i]$ in uncertainty FLC are SM = [0.06893 -

2.03 -0.08586], MS = [-0.1388 -3.735 0.2489], M=[-3.118 -1.124 -0.1342], SL=[3.192 -1.115 -0.0763], ML= [0.6862 -1.122 0.3739], and L= [-0.747 -1.305 -0.4681]. The coefficient sets [p_i k_i] in Reference FLC are Lw = [-0.3877 0.5619], LwS= [0.04266 0.2526], MS= [1.468 2.519], M=[-0.7247 0.7374],SM= [0.2489 0.4429], MM= [-0.1911 0.3953], and L = [-1.329 -0.8895].

The fuzzy rules in uncertainty FLC are

(1) If RH is PL and ERH is PS then IG is SM
(2) If RH is NL and ERH is NS then IG is MS
(3) If RH is NS and ERH is PL then IG is M
(4) If RH is NM and ERH is NM then IG is SL
(5) If RH is PS and ERH is PM then IG is ML
(6) If RH is PM and ERH is NL then IG is L.

where RH, ERH, and IG are references of heading, error rate of heading, and an amount of incremental gain, respectively.

Also in Reference FLC are

(1) If RH is PM then IGSF is Lw
(2) If RH is NM then IGSF is LwS
(3) If RH is ZR then IGSF is MS
(4) If RH is PS then IGSF is MM
(5) If RH is NL then IGSF is SM
(6) If RH is PL then IGSF is LM
(7) If RH is NS then IGSF is L

where IGSF is an amount of incremental gain value at a standard friction coefficient.

C. The implication method (AND method) is applied to each rule to reshape the membership function of the consequent based on the weight value in the antecedents of the rule.

D. Aggregation of all the output in each rule is made by combining the reshaped the membership functions in consequent part of each fuzzy rules. The aggregation is done by taking the maximum value in the output of rules.

E. In defuzzification of the aggregated output in order to result into a single number in the universal discourse of output fuzzy sets. We use the centroid calculation which returns the centroid area under the curve of an aggregated membership function of all the rules. As the results of the process of fuzzy inference with the given fuzzy sets, fuzzy rules, and the related internal optional methods in our application, we have gotten the functional surface and a plot of ANNFLC as in Figure 7.

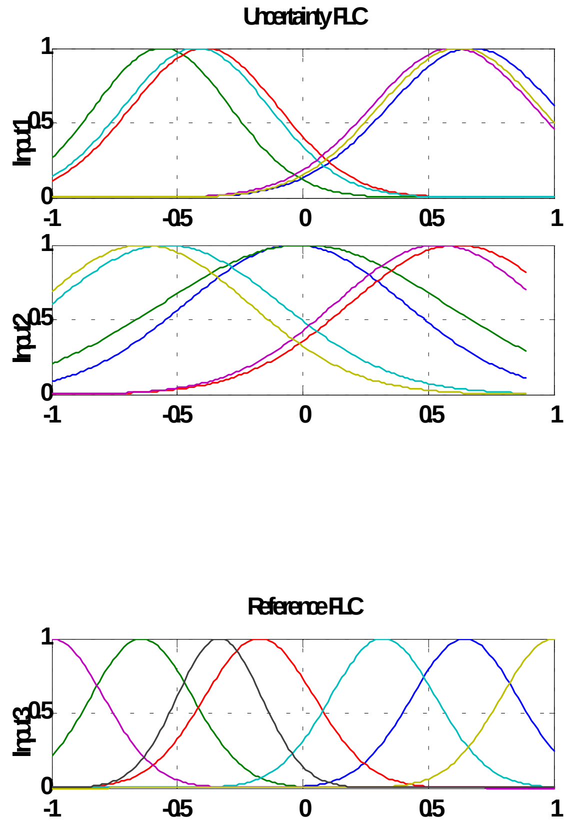

Figure 6. The Membership Function in Input Fuzzy Sets

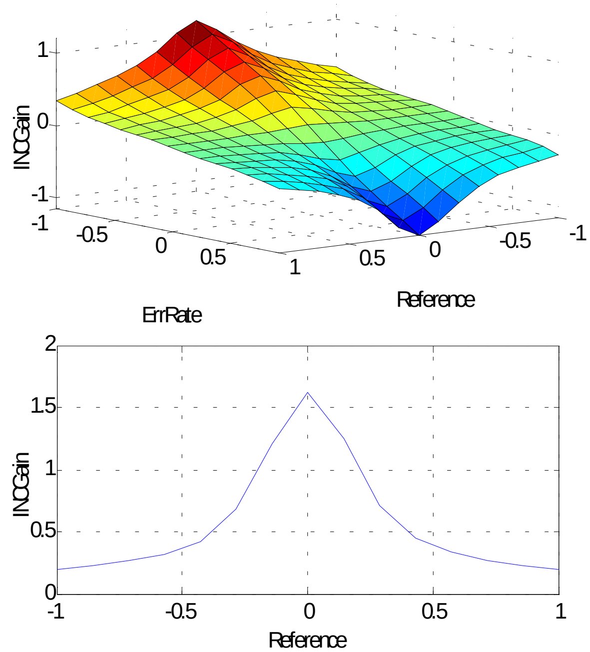

Figure 7. Function Surface of ANNFLC

6. Example Simulation

A controller was designed for waypoint maneuvers in which the controlled vehicle must pass through a sequence of prescribed coordinates. Given initial and desired waypoints, our proposed strategy was to follow the line connecting the two points onto the horizontal plane without unstable tracking patterns and with constant speed. The hybrid controller is evaluated by comparison with a PID-only controller. The responses of the control system with PID controller are tested at the different desired heading references:{0.3, 0.6, 1.0, 1.4} radians by changing the four different values of uncertainty in {0.5, 0.8, 1.2, 1.8} as seen in the first plots of Figure 8.

The PID controller is designed for a nominal operating condition corresponding to a desired heading of 0.9 radian, an uncertainty coefficient of 0.9, and a speed regulator aimed to keep a constant velocity of 1.5ft/sec.

Under the same conditions of the PID-only controller, the responses of the hybrid control system are evaluated and the results shown in the second plots of Figure 8.

7. Conclusion

The simulation results show that the hybrid controller reduces the mean errors between the reference heading and actual ones disturbed by the uncertainties. The hybrid controller developed under this effort shows superior performance to the PID-only controller.

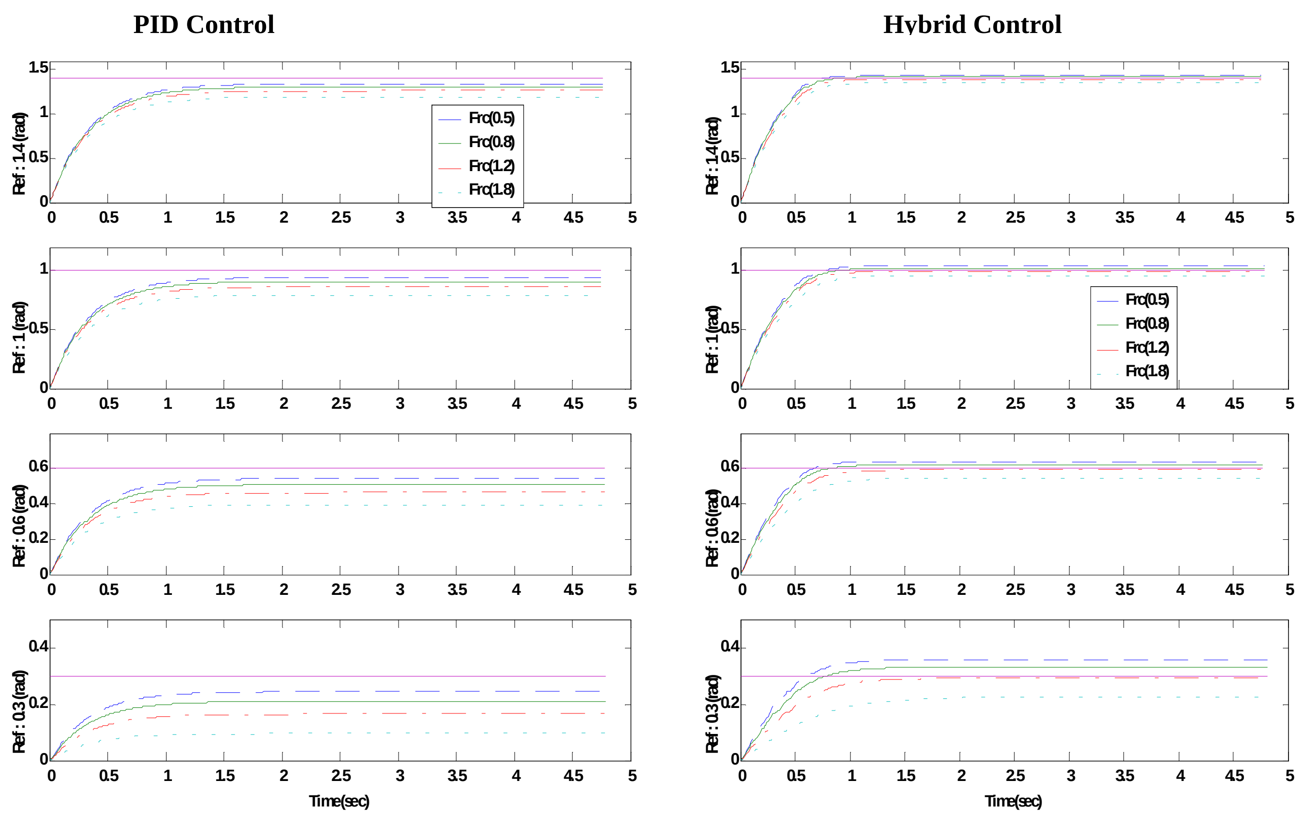

Figure 8. The Comparison of the Result of Simulation between PID Controller and the Proposed Hybrid Controller

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