International Journal of Current Engineering and Technology
E-ISSN 2277 – 4106, P-ISSN 2347 – 5161
Available at http://inpressco.com/category/ijcet

Research Article

BFA optimized intelligent controller for path following unicycle robot over irregular terrains

Abdullah Almeshal†*, Khaled Goher‡, Mohammed R. Alenezi†, Ahmad Almazeed†, Jamal Almatawahξ, Muhammad Moaz† and Najat Al-rashed

†Electronics Engineering Technology Department, College of Technological Studies, Public Authority for Applied Education and Training (PAAET), Kuwait

‡ Institute of Biomedical Technologies, Auckland University of Technology, Auckland, New Zealand

ξCivil Engineering Technology Department, College of Technological Studies, Public Authority for Applied Education and Training (PAAET), Kuwait

Received 05 March 2015, Accepted 08 April 2015, Available online 20 April 2015, **Vol.5, No.2 (April 2015)**

Abstract

This paper presents the performance of applying a bacterial foraging optimisation algorithm (BFA) algorithm on an intelligent controller for a unicycle class of differential drive robot. Previous studies have focused on regular terrains. In this work, an intelligent hybrid fuzzy logic controller is developed and implemented for the unicycle robot to follow a predefined trajectory on an irregular rough terrain of concrete and gravel. The controller gains and scaling factors where optimised using BFA to minimise the overall system mean square error. Simulations have shown the effectiveness of the control method in achieving a good convergence towards the optimal gains on the irregular rough surfaces.

Keywords: *unicycle robot, path tracking, BFA, optimization, fuzzy logic controller.*

1. Introduction

Differential drive robots have been of great interest to many researchers due to their instable and coupled nature that serves as a test platform for various control strategies. Designing a proper stabilization controller requires an inevitable need to model the differential drive robot and understand its performance towards the desired trajectories. A differential drive wheeled mobile robots has two wheels that can turn at different rates by which it manoeuvres.

Various controllers have been developed and adopted by researchers on controlling the differential drive robot. (Jiang, *et al*, 2005) presented a new tracking method for a mobile robot by combining predictive control and fuzzy logic control. A predictive controller was used to overcome the time delay caused by the slow response of the sensors. In addition, fuzzy control was used to deal with the non-linear characteristics of the system. Experimental results demonstrated the feasibility and advantages of this predictive fuzzy control on the trajectory tracking of a mobile robot.

A dynamic-model-based control scheme for balancing and velocity control of a unicycle robot was presented by (Han, *et al,* 2015). The authors used the Euler-Lagrange equation to derive the dynamic equations of the unicycle robot to implement dynamic speed control. To achieve real-time speed control, a sliding-mode control and a nonzero set-point linear quadratic regulator (LQR) was utilized to guarantee stability while maintaining the desired speed-tracking performance. The authors also used a sigmoid-function-based sliding-mode controller to minimize switching-function chattering. An LQR controller has been implemented for pitch control to drive the unicycle robot to follow the desired velocity trajectory in real time using the state variables of pitch angle, angular velocity, wheel angle, and angular velocity. The control performance of the two control systems using a single dynamic model was experimentally demonstrated which showed successful results in balancing and velocity control of the unicycle robot.

Fuzzy logic control (FLC) strategy was adopted by (Castillo, *et al*, 2012) and (Martinez, *et al*, 2009) to control a unicycle robot were a FLC based on back stepping control ensures a stable performance of the robot and to drive the unicycle robot toward the reference path with a superior performance.

Based on both the kinematic and dynamic model of a unicycle, (Carona, *et al*, 2008) proposed an inner loop nonlinear controller with a dynamic model controller on the outer loop. The robot was commanded to follow a predefined trajectory that was simulated with

*Corresponding author: **Abdullah Almeshal**

different movement scenarios such as motion stop and circular trajectories. Simulations presented showed a successful control strategy of the unicycle robot.

(Lee, *et al*, 2001) presented a solution to a tracking control problem with saturation constraint for a class of unicycle-modelled mobile robots. The authors formulated and solved using the back-stepping technique and the idea from the LaSalle's invariance principle. The proposed controller can simultaneously solve both the tracking and regulation problems of a unicycle-modelled mobile robot. Computer simulations were presented which confirmed the effectiveness of the proposed tracking control law. Practical experimental results validated the simulations.

An intelligent control approach was presented by (Lee and Chiu, 2013) for a differential drive robot were a higher level navigation controller combined with a lower level fuzzy logic based controller was designed and implemented for the differential drive robot to be able to stabilise over slopes and manoeuvre in terrains and mazes. The robot was implemented and tested experimentally and proved the feasibility of the controller in achieving the desired trajectories and paths.

(Martins, *el al*,2014) developed an adaptive controller, which utilises a robust updating law to avoid the drifting of the robot and keep the control error in bounded region to overcome instability problems. Simulations and experiments using Pioneer 2-DZ robot platforms showed successful control results.

In this paper, we utilize an optimised intelligent hybrid controller developed by (Almeshal, *et al*, 2013a) and discuss the performance of applying BFA optimisation algorithm on an intelligent controller for a differential drive unicycle robot on irregular terrains. Simulations showing the performance of the optimised controller is presented and analysis showing the superior performance of the optimisation algorithm.

2. The unicycle robot model

The robot considered in this paper is a unicycle mobile robot, reported by (Klancar, *et al*, 2005), and is described by the following equation of motion.

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} cos\theta & 0 \\ sin\theta & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v \\ \omega \end{bmatrix} \quad (1)$$

where,
v is the linear velocity and w is the angular velocity of the robot. The right and left wheel motor velocities can be expressed as $v_R = v + \frac{\omega L}{2}$ and $v_L = v - \frac{\omega L}{2}$ respectively. Given a reference path $(x_r(t), y_r(t))$, the required inputs can be calculated as

$$v_r(t) = \pm\sqrt{\dot{x}_r^2(t) + \dot{y}_r^2(t)} \quad (2)$$

$$\omega_r = v_r(t)\kappa(t) \quad (3)$$

$$\theta_r(t) = arctan2\big(\dot{y}_r(t) + \dot{x}_r(t)\big) + \beta\pi \quad (4)$$

where $\kappa(t)$ represents the path curvature and $\beta = 0.1$ for forward or backward movement. The angular velocity is derived by differentiating equation (4) with respect to time.

$$\omega_r(t) = \frac{\dot{x}_r(t)\ddot{y}_r(t) - \dot{y}_r(t)\ddot{x}_r(t)}{\dot{x}_r^2(t) + \dot{y}_r^2(t)} \quad (5)$$

3. Hybrid fuzzy logic control strategy

Fuzzy logic controllers have proven to be useful in controlling non-linear systems. Although for complex systems, FLC comprises model-free control approach that difficult to be described and modelled mathematically. A hybrid FLC controller was developed by (Almeshal, *et al*, 2013a) and has proven to be efficient in controlling highly nonlinear and coupled robotic vehicle as presented by (Almeshal, *et al*, 2013a, 2013b, 2012a, 2012b) and (Agouri, *et al*, 2013). The advantage of using a hybrid FLC is the way it's designed, where a model free controller is applied to the system where its variables are continuously changing with time. Moreover, it has been widely used in robotic vehicles with properly tuned scaling factors and gains. In this paper, the hybrid FLC is used to control the unicycle robot with proper fuzzy rules tuning and adjustments of the controller gains.

The system consists of two control loops with two hybrid FLC controllers. Each hybrid FLC controller is composed of a proportional-derivative plus integral controller followed by a fuzzy controller that works together to fine tune the control signal. Thus, driving the robot to the desired reference path. The hybrid FLC is presented in Figure 1.

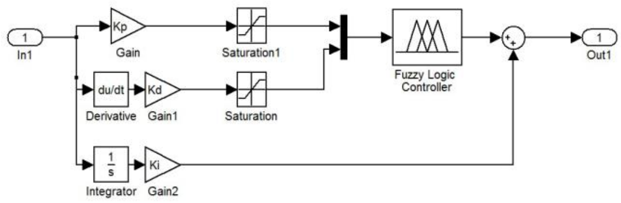

Fig.1 Hybrid fuzzy logic controller block diagram

The fuzzy inference engine is selected to be a Mamdani-type with Gaussian membership functions. This results in smoother output values. The inputs for the hybrid FLC are the error signal, change of error and the sum of previous errors. The fuzzy membership functions are presented in Figure 2.

The linguistic variables describing the inputs and outputs were chosen as Positive Big (PB), Positive Small (PS), Zero (Z), Negative Big (NB) and Negative Small (NS) with 25 fuzzy rule base described in Table 1.

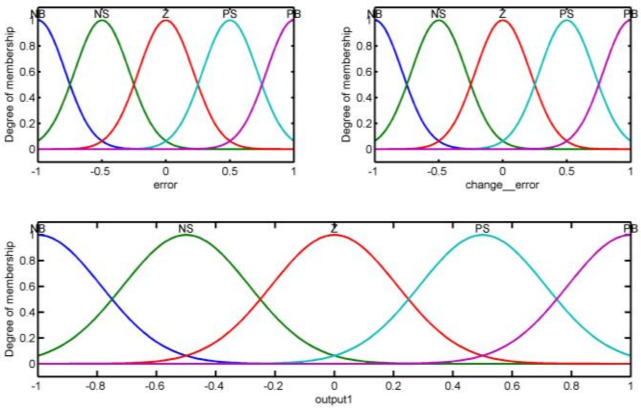

Fig. 2 fuzzy membership functions of the hybrid FLC

Table 1 Fuzzy rules base

e \ e’	NB	NS	Z	PS	PB
NB	NB	NB	NB	NS	Z
NS	NB	NB	NS	Z	PS
Z	NB	NS	Z	PS	PB
PS	NS	Z	PS	PB	PB
PB	Z	PS	PB	PB	PB

In order to achieve optimal controller gains of the hybrid FLC with minimum overall system errors, a hybrid spiral dynamics bacterial chemotaxis optimisation will be adopted. In the next section, the BFA will be integrated into the control system.

4. Bacteria Foraging optimisation Algorithm (BFA)

Bacterial foraging algorithm (BFA) is a biologically inspired optimisation algorithm developed by (Passino, 2000; Passino, 2002). BFA optimisation is inspired by the foraging strategy of Escherichia Coli (E. Coli) bacteria that lives in human intestine. The optimisation process mimics the way that bacteria searches for areas with high nutrient and avoid areas with toxins. The E. Coli uses a series of movements that enables it to swim and search for nutrients. Each E. Coli bacterium has a body and flagella that allows swimming and change its direction by tumbling.

As reported by (Passino, 2002), the bacteria swim continuously in the medium to search for the high nutrient areas. If the area is noxious, the bacterium releases repellent chemical substance and tumbles to get away from the noxious area. In neutral areas, where there are neither nutrients nor noxious, the bacteria continuous tumbling more frequently to change the direction and search for better nutrient-rich areas. If the area has high nutrients, the bacteria continuous swimming in the same direction in and releases attractant for other bacteria in the medium. The bacteria have an exponential growth rate that motivated researchers to model it as an optimisation method. The bacteria with high fitness reproduce and bacteria and others eliminated in order to reach the high-nutrient mediums quickly and accurately.

These processes were modelled via a series of continuous processes defined as chemotaxis, swarming, reproduction, and elimination and dispersal events. Table 2 represent the nomenclature of the parameters that will be used in the optimisation pseudo code in the order they appear.

Table 2 BFA optimisation nomenclature

Parameter	Description
p	The dimension of the search space
S	Total number of the bacteria in the population. S must be even.
Nc	Number of chemotactic steps of the bacterium lifetime between reproduction steps
Ns	Number of the swims of the bacterium in the same direction
Nre	Number of reproduction steps
p_{ed}	Probability of bacterium to be eliminated or dispersed
i=1,2,3,…S	Index of bacterium
j=1,2,3,…Nc	Index of chemotaxis
k=1,2,3,…Nre	Index of reproduction steps
l=1,2,3,…Ned	Index of elimination and dispersal events
m_s*=1,2,3,…Ns*	Index of the number of swims
J	The cost function value
C	Step size of the tumble of the bacterium

The BFA optimisation pseudo code developed by (Passino, 2002) is as follows:

1. Elimination and dispersal loop: for $l = 1, 2, 3, \dots, N_{ed}$ do $l = l + 1$
2. Reproduction loop: for $k = 1, 2, 3, \dots, N_{re}$ do $k = k + 1$
3. Chemotaxis loop: for $j = 1, 2, 3, \dots, N_c$ do $j = j + 1$
- **a.** For $i = 1,2,3 \dots, S$ take a chemotactic step for bacterium i as follows
- **b.** Compute the nutrient media (cost function) value $J(i, j, k, l)$ calculate
  $$J(i,j,k,l) = J(i,j,k,l) + J_{CC}\left(\theta^i(j,k,l), P(j,k,l)\right)$$
  (i.e., add on the cell-to-cell attractant effect to the nutrient concentration). If there is no swarming effect then
  $$J_{CC}\left(\theta^i(j,k,l), P(j,k,l)\right) = 0$$
- **c.** Put $J_{last} = J(i,j,k,l)$ to save this value since a better cost via a run may be found.
- **d.** Tumble: generate a random vector $\Delta(i) \in \Re^{\rho}$ with each element $\Delta_{m_\rho}(i), m_\rho = 1,2,3, \dots, \rho$ a random number on the range $[-1,1]$
- **e.** Move: Let $\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$ be the result in a step of size $C(i)$ in the direction of the tumble of bacterium i
- **f.** Compute the nutrient media (cost function) value $J(i, j+1, k, l)$, and calculate

$J(i,j+1,k,l) = J(i,j+1,k,l) + J_{CC}\left(\theta^i(j+1,k,l), P(j+1,k,l)\right)$

If there is no swarming effect then

$J_{CC}\left(\theta^i(j+1,k,l), P(j+1,k,l)\right) = 0$

g. Swim (note that we use an approximation since we decide behavior of each cell as if the bacteria numbered $\{1,2,\dots,i\}$ have moved and $\{i+1, i+2, i+3, \dots, S\}$ have not; this is much simpler to simulate than simultaneous decisions about swimming and tumbling by all bacteria at the same time):

i. Let $m_s = 0$ (counter for swim length)

ii. While $m_s < N_s$ (if have not climbed down too long)

1. Count $m_s = m_s + 1$

2. If $J(i,j+1,k,l) < J_{last}$ (if doing better), then $J_{last} = J(i,j+1,k,l)$ and calculate

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$$

this results in a step of size $C(i)$ in the direction of the tumble for bacterium i. Use this $\theta^i(j+1,k,l)$ to compute the new $J(i,j+1,k,l)$ as in step f above.

3. Else let $m = N_s$ (the end of the while statement)

h. Go to the next bacterium $(i+1)$ if $i \neq S$ (i.e. go to step b above) to process the next bacterium.

4. If $j < N_c$ go to step 3.

5. Reproduction:

a. For the given k and l, for each $i = 1,2,3 \dots, S$

Let $J^i_{health} = \sum_{j=1}^{Nc+1} J(i,j,k,l)$ be the health of bacterium i (a measure of how many nutrients it got over its lifetime and how successful it was at avoiding noxious substances). Sort bacteria and chemotactic parameters $C(i)$ in an ascending order since that higher cost means a lower health.

b. The S_r bacteria with the highest J_{health} values die and the other S_r bacteria with the best value splot (and the copies that were made are replaced at the same location as their parent)

6. If $k < N_{re}$ go to step 2.

7. Elimination-dispersal: for $i = 1,2,3 \dots, S$ eliminate and disperse each bacterium which has probability value less than P_{ed}. If one bacterium is eliminated then it is dispersed to random location of nutrient media. This mechanism makes computation simple and keeps the number of bacteria in the population constant

For $m = 1{:}S$

If $P_{ed} > rand$ (generate random number for each bacterium and if the generated number is smaller than P_{ed} then eliminate/disperse the bacterium)

Generate new random positions for bacteria

Else

Bacteria keep their current position (not dispersed)

End

8. If $l < N_{ed}$ then go to step 1; otherwise end

4.1 BFA Simulation parameters

Table 3 BFA parameters

P	S	Nc	Ns	Nre	Ned	Ped	Sr
6	40	12	3	3	2	0.3	S/2

4.2 Constrained BFA optimisation

The performance index of the system is chosen as the minimum mean squared error (MSE) of system response. The MSE is calculated for each control loop in the system as follows:

$$MSE\ 1 = \min\left[\frac{1}{N}\sum_{i=1}^{N}(x_d - x_a)^2\right] \quad (6)$$

$$MSE\ 2 = \min\left[\frac{1}{N}\sum_{i=1}^{N}(y_d - y_a)^2\right] \quad (7)$$

The objective function is chosen as the summation of the MSE of the system which can be expressed as the summation

$$J = \min(v_{MSE} + \omega_{MSE}) \quad (8)$$

Hence, minimizing the objective function J will result in finding the optimum control parameters with the minimum mean square error of the overall system response

In order to restrict the optimisation algorithms to search within the feasibility region of the system, which is the stability region of the vehicle, system constraints must be defined to ensure stability.

Constrained optimisation is used to limit the system within the stability region while searching for optimum parameters. The stability bounds are defined by using trial and error and defining a feasible interval for each control parameter; shown in Table 4, that assures the stability of the system.

Table 4 Boundary limits of controller gains

Boundaries	Loop 1			Loop 2		
	Kp	Kd	Ki	Kp	Kd	Ki
Lower	0.1	0.1	0.1	0.1	2	0.05
Upper	33	12	2	50	23	3

Penalty methods are used to convert the constrained optimisation problem into an unconstrained problem by adding a penalty function $P(x)$ to the objective function when the constraint is violated. The cost function of the system can be rewritten as:

$$J(x) = \begin{cases} J(x), & x \in feasible\ region \\ J(x) + P(x), & x \notin feasible\ region \end{cases}$$

Where $J(x)$ represents the cost function and $P(x)$ represents the penalty function. The penalty function is added to the cost function to result in a very high cost whenever a constraint is violated. The penalty function is defined as ten times the cost function of the unfeasible region and zero otherwise. This can be expressed as:

$$P(x) = \begin{cases} 0 & x \in feasible\ region \\ 10.J(x) & x \notin feasible\ region \end{cases}$$

5. Irregular terrain profile modelling

To simulate the robot to drive on various outdoor environments of contrastive frictional profiles, environment modelling must be integrated into the simulation blocks. Environment modelling is based on study of soil mechanics and was reported in literature, specifically in locomotion systems; by many researchers to enable them study the foot-ground interaction forces. Silva *et al*. have used a modified spring-damper dashpot system to simulate different types of grounds to study the foot-ground interaction for locomotion systems. They have presented the modification by changing the parameters of damping and stiffness B and K respectively for both horizontal and vertical deflection forces. The contact of the foot and ground can be described by the nonlinear equations:

$$f_{i\eta F} = -K_{\eta F}(\eta_{iF} - \eta_{iF0}) - B'_{\eta F}[-(y_{iF} - y_{iF0})]^{v_n}(\dot{\eta}_{iF} - \dot{\eta}_{iF0}) \quad (9)$$

$$-B'_{\eta F}\left[-\Delta_{iyFMax}\right]^{v_n} = -B_{\eta F} \quad (10)$$

Where,
$K_{\eta F}$ = Linear stiffness factor
$B'_{\eta F}$ = Nonlinear damping factor
η = Directions in x and y
x_{if0}, y_{if0}= Coordinates of the wheel-ground touchdown
v_n= A parameter dependent on ground characteristics with $0.9 < v_n < 1.0$
Δ_{iyFMax}= Maximum penetration depth of wheel into ground

The linear damping and stiffness parameter values for different ground profiles, extracted from soil mechanics and Young's modulus of elasticity of gravel and sand soil types is presented in Table 5.

Table 5 Young's Modulus of elasticity for gravel and sand soil types

Soil type	K_{xF} (Nm-1)	B_{xF} (Nsm-1)	K_{yF} (Nm-1)	B_{xF} (Nsm-1)
Concrete	2604304130	153097	3410398265	175196
Gravel	17362028	12500	22735988	14305

In this paper, the robot will be simulated on an irregular terrain of concrete and gravel.

6. Simulations and Results

The robot is commanded to track a circular trajectory with a radius of 4 meters on an irregular terrain composed of concrete and gravel distributed randomly. The ground friction profile is distributed randomly over the path to mimic the real life situation. The BFA algorithm has achieved the minimum value of cost function within approximately 90 iterations. The minimum cost function value was found to be 0.344. The cost convergence plot is illustrated in Figure 3.

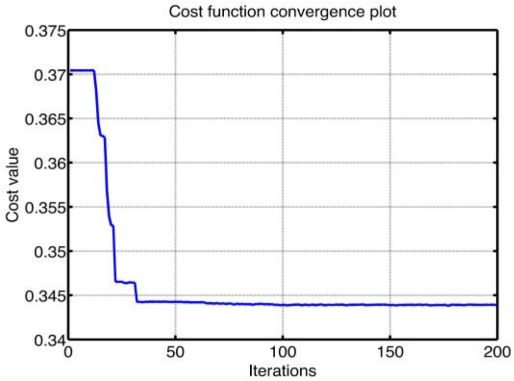

Fig. 3 Cost convergence plot

Figure 4 shows the robot actual path compared against the reference circular path with the heuristically tuned controller gains. It is obvious that the controller is able to track the reference trajectory with high degree of disturbance rejection. However, with the optimised controller gains, a better response and disturbance rejection rate was achieved. The optimised system response is shown in Figure 5. The improvement of the robot response can be noted in overcoming the ground frictional profile and in coping well with the path without having any drift.

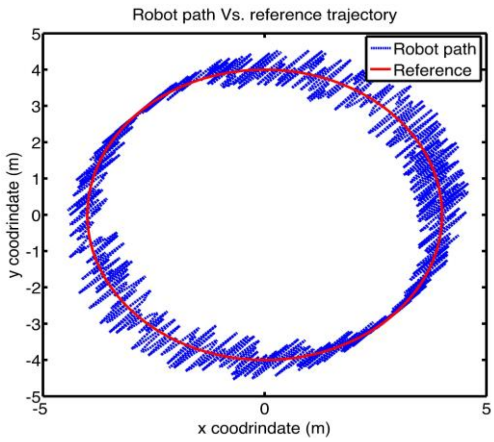

Fig. 4 Robot actual path with the heuristically tuned controller gains

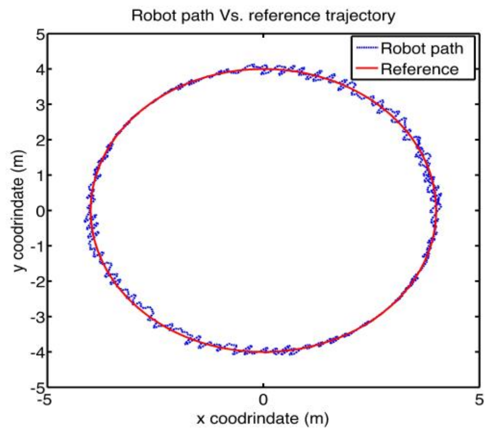

Fig. 5 Robot actual path with the BFA optimised controller gains

Conclusions

This paper has presented the performance of a BFA optimised intelligent hybrid controller to control a unicycle robot over irregular terrains. The intelligent hybrid controller was implemented and evaluated by simulating the system model in MATLAB/Simulink environment. Environment modelling and soil mechanics were utilised to generate the friction profile of different grounds. The intelligent controller was able to drive the robot and force it to follow the predefined trajectory even with heuristically tuned gains. The controller gains have been optimised using BFA optimisation algorithm to minimise the mean square error of the robot system. The performance of the system with the optimised controller gains has been greatly improved proving a successful control and optimisation strategy. Further work will include simulating the robot with a more challenging steering scenario to evaluate the robustness of the utilised controller.

Acknowledgment

The author appreciate and thank the State of Kuwait and the Public authority for applied education and training (PAAET) for their continuous support.

References

A.M.Almeshal, K.M.Goher, M.O.Tokhi, (2013a), Dynamic modelling and stabilization of a new configuration of two-wheeled machines. *Robotics and Autonomous Systems*, 61(5), 443–472.

X.Jiang; Motai, Y.; Zhu, X., (2005), Predictive fuzzy logic controller for trajectory tracking of a mobile robot, *Soft Computing in Industrial Applications, Proceedings of the 2005 IEEE Mid-Summer Workshop on* , pp.29-32.

Ti-Chung Lee, Kai-Tai Song, Ching-Hung Lee, and Ching-Cheng Teng, (2001), Tracking control of unicycle-modeled mobile robots using a saturation feedback controller. *IEEE Transactions on Control Systems Technology*, 9(2), pp.305-318.

Han, S.I., Lee, J.M., (2015), Balancing and Velocity Control of a Unicycle Robot Based on the Dynamic Model, *Industrial Electronics, IEEE Transactions on* , vol.62, no.1, pp.405-413.

R.Carona, A.P.Aguiar, J.Gaspar, (2008), Control of unicycle type robots tracking, path following and point stabilization.

M.F.R.Lee, F. H. S.Chiu, (2013), Intelligent multi-behavior control and coordination for the autonomous differential drive mobile robot, *In IEEE International Conference on Fuzzy Theory and Its Applications (iFUZZY),*pp. 31-36.

Martins, F. N., Celeste, W. C., Carelli, R., Sarcinelli-Filho, M., & Bastos-Filho, T. F. (2008). An adaptive dynamic controller for autonomous mobile robot trajectory tracking. Control Engineering Practice, 16(11), pp.1354-1363.

Castillo, O., Martínez-Marroquín, R., Melin, P., Valdez, F., & Soria, J., (2012), Comparative study of bio-inspired algorithms applied to the optimization of type-1 and type-2 fuzzy controllers for an autonomous mobile robot. Information Sciences, 192, pp.19-38.

Martínez, R., Castillo, O., & Aguilar, L. T., (2009), Optimization of interval type-2 fuzzy logic controllers for a perturbed autonomous wheeled mobile robot using genetic algorithms. Information Sciences, 179(13), 2158-2174.

Almeshal, A. M., Goher, K. M., Tokhi, M. O., Sayidmarie, O., Agouri, S. A., (2012a), Hybrid fuzzy logic control approach of a two wheeled double inverted pendulum like robotic vehicle, *Adaptive Mobile Robotics - Proceedings of the 15th International Conference on Climbing and Walking Robots and the Support Technologies for Mobile Machines, CLAWAR 2012*, pp. 681–688.

Agouri, S. A., Tokhi, O., Almeshal, A., Sayidmarie, O., & Goher, K. M., (2013), Modelling and control of two-wheeled vehicle with extendable intermediate body on an inclined surface, *Proceedings of the IASTED International Conference on Modelling, Identification and Control*,pp. 388–393.

Almeshal, A. M., Tokhi, M. O., & Goher, K. M., (2012b), Robust hybrid fuzzy logic control of a novel two-wheeled robotic vehicle with a movable payload under various operating conditions, *Proceedings of the 2012 UKACC International Conference on Control, CONTROL 2012*,pp. 747–752.

Almeshal, A. M., Goher, K. M., Nasir, A. N. K., Tokhi, M. O., Agouri, S. A., (2013b), Hybrid spiral dynamic bacterial chemotaxis optimisation for hybrid fuzzy logic control of a novel two wheeled robotic vehicle, *Nature-Inspired Mobile Robotics: Proceedings of the 16th International Conference on Climbing and Walking Robots and the Support Technologies for Mobile Machines, CLAWAR 2013*,pp. 179–188.

Nasir, A. N. K., Tokhi, M. O., Ghani, N. M., Ahmad, M. A., (2012), A novel hybrid spiral dynamics bacterial chemotaxis algorithm for global optimization with application to controller design, *UKACC International Conference on Control (CONTROL 2012)*,pp. 753–758.

Tamura, K., & Yasuda, K., (2011), Primary study of spiral dynamics inspired optimization, *IEEJ Transactions on Electrical and Electronic Engineering*, *6*(S1), S98–S100.

Passino, K. M. (2002). Biomimicry of bacterial foraging for distributed optimization and control, *IEEE Control Systems*, *22*(3), 52–67.

Klancar, G., Matko, D., Blazic, S., (2005), Mobile robot control on a reference path. In Intelligent Control, *Proceedings of the 2005 IEEE International Symposium on*, Mediterrean Conference on Control and Automation (pp. 1343-1348).