IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Parametric Investigation on Neuromorphic Humanoid robotic control system using deep learning over Recurrent neural network algorithm for nonlinear regression dynamic fitting in Neural schema

Single Author: Dr. Ashok Kumar Ramadoss ,
MCA, MBA, MSc. Mat Sc., Ph. D, (International Award winner and Senior Member of Robotics)
Associate Professor, Coimbatore Institute of Technology, Anna University Chennai, Scientist, Software engineer, Senior Member in UACEE, New York and Hong Kong Society of robotics and automation and Currently Member in Society of Robotics Surgery, Orlando, Florida,

Abstract: This research signifies the representation of the degrees of association and the non monotonism fuzzy relations and the properties of relation with corresponding approximation using fuzzification characteristics are also analyzed. Humanoid learning with these algorithms allow robots to identify patterns, make predictions, and improve their performance over time, making them more versatile and effective in a wide range of applications, sufficiently of humanoid learning. is needed to arrive an objective point with no collision with obstacles in the static or dynamic environment, Adaptive fusion strategy in needed for selecting sensor information, Nonmonotonic reasoning plays an important role in the development of artificial intelligent systems that try to mimic common sense reasoning, as exhibited by humans in slow and steady but the error is minimized unlike in monotonic where the decision is fast but with more errors.

Keywords: Quantization, minimal perceivable difference, threshold of perception, psychometric experiment. Dynamic fitting,neural weights, neural schemas, genetic algorithms

1. Introduction

On the other hand, a hybrid learning system provides an explanation capability to trained Neural Networks through acquiring symbolic knowledge of a domain, refining it using a set of classified examples along with Connectionist learning techniques and, finally, extracting comprehensible symbolic information with the control system using fuzzy inference for the fit of dynamic robotic control system which uses edge computing over convolutional neural networks. The second goal of this research is to propose a methodology to quantize the impact of single or multiple parameters out of these fields on perceived Humanoid Learning. Prior to quantization, the minimal perceivable difference, that is the threshold of perception is determined for the parameters of interest experimentally[1-4]. Thereafter, these parameters are modified in whole-numbers multiple of the threshold of perception to investigate their influence on perceived humanoid learning. This methodology was on parameter field movement as well as on the parameter distance and movements. Results revealed that the perceived humanoid learning is more sensitive to changes in sequencing than to changes in distance[5-8]

2 Need of the Study - Significant Statement

The movement of the manipulation is a systematic exploration of the proposed network of humanoid learning in order to determine Alpha Ramda humanoid robot was in the trajectory robot paths. In this case of locomotion of robot paths, [9] the path itself had a substantial impact on the result thus making the robot to predict [10] and come out with a decision to turn back after recognizing the obstacles in patterns. parameters seen based on the results of the experimental investigations.[11-14]. Based on the arrived results it is significant that evaluation for different directions in a different way.

3 Inspired basic research – Description

Neural schema is a mechanism to enable the development and execution of complex behaviours in autonomous robots involving adaptation and learning using sophisticated software architectures[15].

4. Problem addressed to real world

Here the problem is the Behaviour based systems arrangement in robot controllers into a collection of task achieving behavioural modules that when properly enumerated only [16-19]

can produce robust results that are repeatable and reliable. To solve this a solution to be developed for the result is a mechanism that uses its own experience and abilities to learn about its world by creating new nodes and links that embody new knowledge that effect that environment[20,21]

5. Basic Research – Understanding

Recognition is done using Recurrent neural network in bringing the access to data sensitization[22-26] by bringing the deep learning concept where all the layers of the nodes are used for transforming the data and then analysing the data for data patterns brings the voice recognizing so that the decision can be predicted sooner[27,28]

6. RESEARCH METHODOLOGY (Protocols adopted)

6.1 Fuzzy Inference rules algorithm for nonlinear regression Dynamic fitting

Let p = 0 and let S$\boldsymbol{S}^{(\boldsymbol{p})}$be a given schedule.

i. For all i, j $\boldsymbol{\epsilon}$ $\boldsymbol{N_n}$, determine the maximum transfer times $\boldsymbol{m_i^j}(\boldsymbol{p})$ in schedule$\boldsymbol{S}^{(\boldsymbol{p})}$.

ii. Identify a route pair r, s with the largest transfer time ($\boldsymbol{m_r^s} = \widehat{\boldsymbol{m}}$).

iii. Applying relevant inference rules to the point pair r, s (i.e., m =$\boldsymbol{m_r^s}$), which results in a new schedule denoted by$\boldsymbol{S}^{(\boldsymbol{p+1})}$.

iv. For all i, j $\boldsymbol{\epsilon N_n}$ determined, the maximum transfer time $\boldsymbol{m_i^j}$(p+1) in schedule $\boldsymbol{S}^{(\boldsymbol{P+1})}$ and calculate the difference as, $\boldsymbol{D}^{(\boldsymbol{p})}$ = $\sum_{\boldsymbol{i,j\epsilon N_n}}[\boldsymbol{m_i^j}$(p) - $\boldsymbol{m_i^j}(\boldsymbol{p}+\boldsymbol{1})]$.

v. If $\boldsymbol{D}^{(\boldsymbol{p})}$ > 0, increase p by one and go to (step 2).

vi. If $\boldsymbol{D}^{(\boldsymbol{p})} \leq \boldsymbol{0}$, and at least one point pair has not been examined yet, choose a point pair r, s with the next largest transfer time otherwise, terminate the algorithm.

7 Fuzzifying the back propagation learning algorithm

All real numbers that characterize a classical neural network become fuzzy [29.30] numbers in its fuzzified counterpart. If the inputs to network and outputs of neural at hidden layers are O $0N_k$, of a neuron, then the inputs $X_{k0}X_{k1,\dots,}X_{kn}$, the weights $W_0, W_{1,\dots,}W_n$ and the output Y_k of this neuron are all fuzzy numbers. The output of each schema, is given in equation Y_k=$S_\beta(\sum_{j=0}^{n} W_j\ X_{kj})$, where S_β is a sigmoidal function for the chosen value.

Thus the parametric investigation in the neuromorphic humanoid robot control system using deep learning in the non linear regression of dynamic fitting gives the option for selecting the data points in the non linear curve in a parabolic place where all the data points lies over the curve of non linear fitting so that the deep learning data are brought together with the parent node so that the decision and the prediction in recognizing the data patterns are done fast with great accuracy.

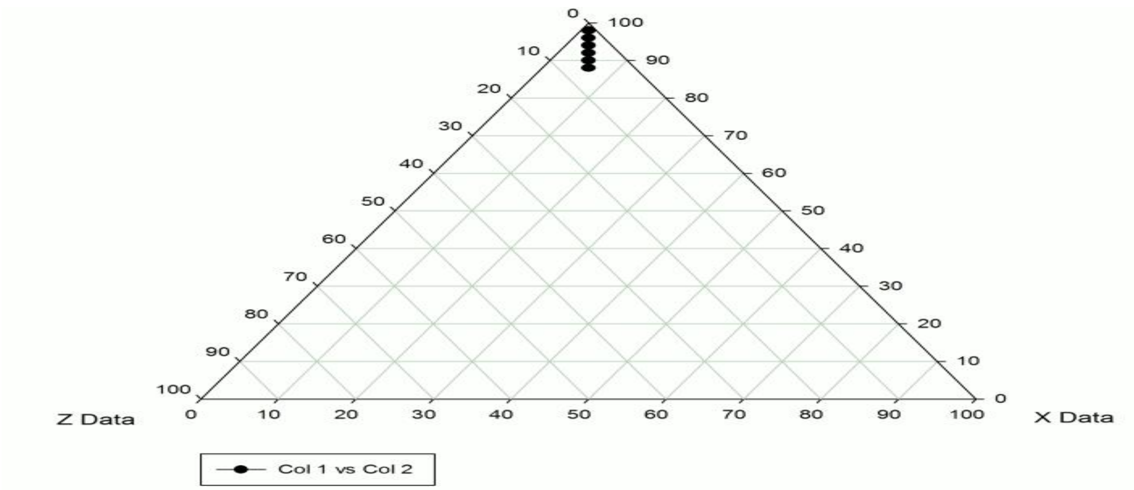

Figure 1. Fuzzy values plotted for various neural weights and neural Schemas

The steepness parameters $\beta, W_j X_{kj}$ is the designate fuzzy number and the sum is $A_k = \sum_{j=0}^{n} W_j \ X_{kj}$ are calculated by fuzzy arithmetic and the output of the neuron obtained is determined by using the extension principle[31].

Error functionE_p, is employed in analysis of the detailed enumeration for both crisp and the Non Monotoncity in fuzzy relations and fuzzy values plotted for various neural weight and neural schemas are specified in Figure 3.1

8 Neuromorphic robotic control system using back propagation algorithm

The proposed back propagation learning algorithm in a fuzzy network with m outputs for each training sample p, as shown in Figure 3.2 is defined by the equation

$$E_p = \frac{1}{2}\sum(T_K^p - Y_k^p)^2, \lambda = \frac{1}{2}\sum_{k=1}^{n}((t_{k_2}^p - t_{k_1}^p)^2 \qquad (3.1)$$

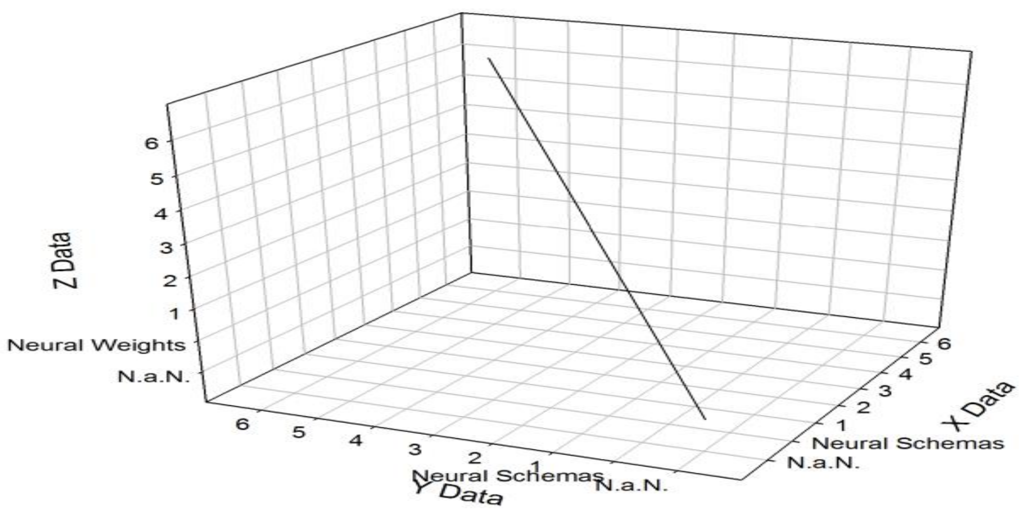

Figure 2 Fuzzy membership functions on neural schema with neural Weight

Here, fuzzy membership functions on neural schema with neural weights showing X and Y directions for neural

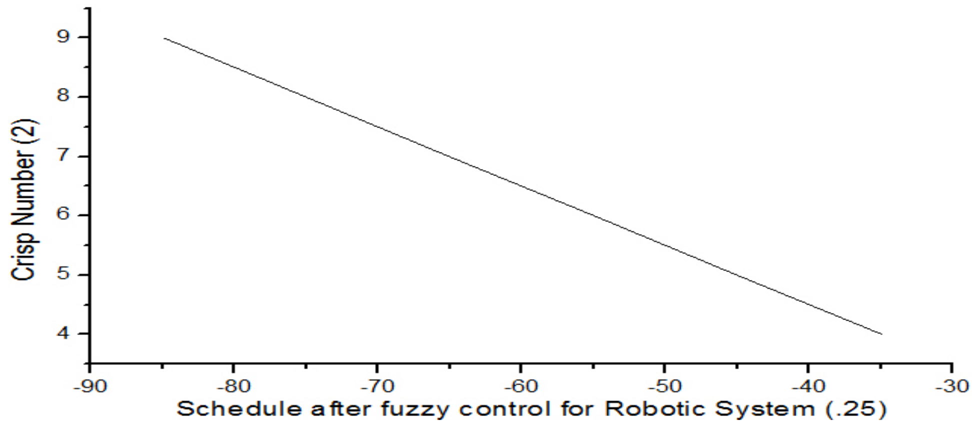

Figure 3 Investigation on Non monotone relations with the Enumeration in membership functions (Fuzzy sets of Robotics system)

9. Investigation on Non monotone relations

Schemas and Z direction for neural weights were all found to be maximum at a value 6 as shown in the Figure 3.2.In the proposed work the analysis of control logic are made with relevant to the input and output variable of the Humanoid Robotic controller in the design of fuzzy logic controller and the ranges of their values are selected as the linguistic states for each variable and expressed by appropriate fuzzy sets as specified in equation 3.1 which is given in the Figure 3.3 as maximum value of 9 as crisp number and a minimum of -35 for schedule after fuzzy control which shows Fuzzy are Non Monotonic in Relations.

10. Results

10.1 Enumeration of fitness by Genetic Algorithm (GA)

$$\dot{x}(t) = Ax(t) + Bu(t),\ y(t) = Cx(t) \qquad (3.2)$$

Where $\dot{x}(t)$ is the state vector, u (t) is the input torque vector, y (t) is the measurement vector, $x(t)$ is the direction vector.
Each matrix is as follows

$$A = \begin{bmatrix} a_1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & a_2 \end{bmatrix}, \quad B = \begin{bmatrix} a_1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & a_2 \end{bmatrix},$$

$$C = \begin{bmatrix} a_1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & a_2 \end{bmatrix}, \text{ With}$$

$$a_1 = \frac{-2c}{Mr^2+2I_w},$$

$$a_2 = \frac{-2cl^2}{I_v r^2+2I_w l^2},\ b_1 = \frac{kr}{Mr^2+2I_w},$$

$$b_2 = \frac{krl}{I_v r^2+2I_w l^2},$$

$$f_1 = \frac{D_{max} - D}{D_{max}},$$

$$f_2 = \frac{\pi - |\Psi|}{\pi},\ f_3 = \frac{d_{max} - d}{d_{\max - 0.01}},\quad f_4 = \frac{\pi - |\psi|}{\pi},$$

Where, a_1, a_2 Is the angular velocity. b1, b2 is the angular acceleration. f_1 is the Neural Weight function, f_2 is the Neural Schema function, f_3 is the Objective Behaviour, f_4 is the Objective point, c is the quantization value, l is the length of the movement, I_v initial velocity, r is the radius vector, I_w Initial mass, π a constant, k is the quantization variable, D is the total distance traveled, d is the distance traveled per unit time, ψ fuzzification behaviour, D_{max} is the maximum trajectory distance.

Therefore by implementing the back propagation algorithm it was fount that the error has been minimized where the neural weights has been adjusted using the neural networks multiple layer perception with arriving the datas in terms of predictive outcome with real decision making to use the normalized quanitized and optimized data in the below sections of training using the deep learning algorithm where all the data sets were trained from the input values to recognize the logical patterns of behaviour in the humanoid robot , thereby the ALPHA RAMDA can taked its own human decision and acts independently.

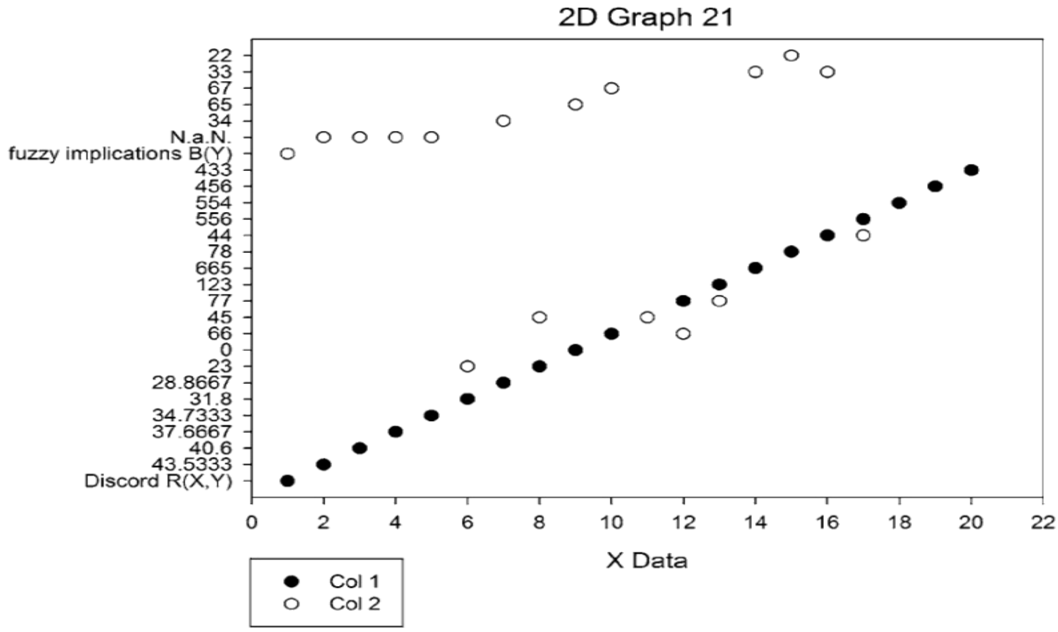

Figure 4 Maximum values of possibility discord (circles) and Possibility strife (diamonds) in fuzzy implication

The role of the objective behaviour group is to control the Humanoid robot so as to arrive in the equation 3.2, at an objective point. The fitness of GA considered here is given by

$$fitness_{ob}=\sum_{i=1}^{n_0}(w_{od}\ X\ D_{fit}^{i}+w_{ot}\ X\ time_{fit}^{i}+\ w_{or}\ X\ road_{fit}^{i}+\ w_{obd}\ X\ B_{d_{fit}}^{i}+\ w_{oba}\ X\ B_{a_{fit}}^{i}) \quad (3.3)$$

With

$$D_{fit}^{i}=\frac{sensor_{ob}-D_{end}^{i}}{sensor_{ob}},\ time_{fit}^{i}=\frac{t_{max}-time_{end}^{i}}{t_{max}},$$

$$road_{fit}^{i}=\frac{sensor_{ob}-road_{end}^{i}}{sensor_{ob}},\ B_{d_{fit}}^{i}=\frac{\tau_{max}-\sum_{j=1}^{n_{r0}}\left|B_{d}^{i}(j)\right|}{\tau_{max}},$$

$$B_{a_{fit}}^{i}=\frac{\tau_{max}-\sum_{j=1}^{n_{r0}}\left|B_{a}^{i}(j)\right|}{\tau_{max}},$$

Where n_0 is the number of training conditions, τ_{max} is the maximum torque force, $B_a^i(j)$ movement of inertia in the initial acceleration in the object j, D_{fit}^i is the evaluation of distance D_{end}^i between the final position of robot and the objective point, $time_{fit}^i$ is the evaluation of convergence time $time_{end}^i$ using the maximum moving time t_{max}, $road_{fit}^i$ is the evaluation of moving distance, $B_{d_{fit}}^i$ and $B_{a_{fit}}^i$ are the evaluation of the consequent part of fuzzy rules in equation 3.3. The number of fuzzy rules is n_{r0} and w_* are weighing parameters of evaluations and fuzzy behaviour based robotic control system with Neuromorphism using back propagation algorithm and genetic algorithm. Maximum values of possibility discord (circles) for fuzzy implications are seen at 456 and possibility strife (diamonds) in fuzzy implication are seen at 22, which shows that 4.8% of fuzzy implications is obtained shown in Figure 3.4.

10.2 Training Process

Training Process were given to access an extensive library of robots directly from RoboDK. The RoboDK library includes:
Over 500 industrial robot arms External axes such as 1, 2 or 3 axis turntables and linear rails, Here it is easily model and synchronize additional axes to find the robot in the RoboDK library Table 3.1 shows the fuzzy based algorithm made a percentage improvement in schedule after fuzzy control as 21% in m and schedule after enumeration was 3.3% r/s in only 34.07 m and 501 m/s of CPU time. Thus the non monotone relations are investigated. Thus GA is enumerated as enumeration of fitness of Genetic Algorithm and the training results are illustrated in Table 3.1 with 15685 r/s as total maximum scheduling time. Mobile robot is achieved for the training conditions and the evaluation of Convergence time.

Table 1 Comparison of results obtained for the scheduling problem by fuzzy based algorithm and enumeration method

Crisp Number	Fuzzy Relation (m)	Layover time at enumeration point (t max)	Initial Schedule for robotic system(r/s)	Schedule After Fuzzy Control for robotic system (m)	Schedule after Enumeration (r/s)
1	20	8	5,25,45	3,23,43	5,25,45
2	60	6	5	5	5
3	60	12	0	17	0
4	30	23	0,30	7,37	0,30
5	30	20	11,41	11,41	11,41
6	60	13	5	23	5
7	30	10	25,55	4,34	25,55
8	30	7	16,46	7,37	16,46
9	60	9	25	6	25
10	60	16	35	8	35
11	60	12	55	20	55
12	15	4	10,25,40,55	14,29,44,59	10,25,40,55
13	60	9	30	7	30
14	30	6	8,38	8,38	8,38
15	15	13	6,21,36,51	6,21,36,51	6,21,36,51
16	20	2	0,20,40	19,39,59	0,20,40
17	60	0	12	1	12
18	60	0	9	16	9
19	30	0	21,51	0,30	21,51
20	60	0	34	16	34
21	20	0	19,39,59	19,39,59	19,39,59
22	15	0	13,28,43,58	16,31,46	13,28,43,58
23	30	0	15,45	3,33	15,45
24	60	0	22	7	22
25	30	0	24,54	1,31	24,54
Total Max. Scheduling Time X data			**15685 r/s**	**12630 m**	**15255 r/s**
Percentage Improvement Y data			**-**	**21%**	**3.3%**
Computation-Scheduling Time(CPU secs)			**-**	**34.07**	**501**

Thus non monotonism for the existing relations was made to preserve some of the properties of relation that all pairs have corresponding approximation using fuzzification characteristics. Enhancement of the non monotone neural schema was done by comparing using approximation with fuzzy logic controller. Fuzzy Neural Schema was assessed by quantization. In the proposed work Cognitive Neuromorphic humanoid robotic control system is evaluated by investigating acceleration capabilities as well as in the trajectory robot paths..It is observed that for a maximum neural weight the corresponding neural schema was obtained which is an average value obtained for neural schemas which proved that for a maximum neural weight the neural schema is consistent and perfect without any data maximum or minimum values with the parameter settings in semantics.

11. Outcome

A detailed mechanism adopted for the development and execution of complex behaviours namely neural schema was studied. Experimental techniques and the research methodologies used in the fuzzy inference rules algorithm for nonlinear regression dynamic fitting were studied. Fuzzifying the back propagation learning algorithm characterizing the neural network with the explanation with neurons was studied.

12. Conclusion

The calculation of steepness parameters and the output of the neuron are determined. Fuzzy behaviour based robotic control system with neuromorphism with the proposed back propagation learning algorithm was studied. The analysis of control logic in the design of the humanoid robotic fuzzy logic controller was done with the linguistic states. Fuzzy membership functions on neural weights and neural schema were plotted. Enumerations of fitness by GA were designed by using training process.

13. Future Work

The training results during the trajectory mobile robot obtained and the overcome of obstacle using the fusion method with fuzzy logic controller in several reactive learning environments is presented. Analysis of the state vector to be incorporated as a protocol and the result obtained for the scheduling problem by fuzzy based algorithm and enumeration method to be analyzed arriving the tracking results as discussed.

14.Conflict of Interest Statement

There is no co-authors and I agree with myself of my own knowledge there is no financial interest to report and there is NO Fund, All the datas are collected, analyzed and interpreted data by me alone

15. Declarations:

Availability of data and material (data transparency):

On request it can be given.

Competing interests:

The authors have no financial or proprietary interests in any material discussed in this article.

The author did not receive support from any organization for the submitted work

Funding

The author have no relevant financial or non-financial interests to disclose. I am a Single author, There are no authors involved in this research. The author have no financial or proprietary interests in any material discussed in this article. The author did not receive support from any organization for the submitted work.

No funding was received to assist with the preparation of this manuscript. No funding was received for conducting this study. No funds, grants, or other support was received, No interest in the subject matter or materials discussed in this manuscript.

Authors' contributions

AKR is a Single Corresponding Author, No authors were involved in research, All contributions like, analysis, problem identification, problem deifinition, design, Implementation, experimental methods all were done by sole corresponding author

Acknowledgements

Referred as per References

References

[1].Inverse Kinematics of Human Arm Based on Multisensor Data Integration. Mihelj (B) et al J Intell Robot Syst (2006) 47: 139–153 Elsevier ,Faculty of Electrical Engineering, University of Ljubljana . 25, SI-1000 Ljubljana, Slovenia, J Intell Robot Syst (2006) 47: 139–153,DOI 10.1007/s10846-006-9079-8,e-mail: J Intell Robot Syst (2006) 47: 139–153 DOI 10.1007/s10846-006-9079-8Stoytchev A (2011) Self-detection in robots: a method based on detecting temporal contingencies. In: Robotica. Cambridge University Press, Cambridge.

[2] . Lee J, Kiser J, Bobick A, Thomaz A (2011) Vision-based contingency detection. In:ACM/IEEE international conference onhuman-robot interaction (HRI).

[3]. Lohan K, Vollmer A, Fritsch J, Rohlfing K, Wrede B (2009) Which ostensive stimuli can be used for a robot to detect and maintain tutoring situations? In: ACII workshop

[4]. Pitsch K, Kuzuoka H, Suzuki Y, Sussenbach L, Luff P, Heath C (2009) The first five seconds: Contingent stepwise entry into an interaction as a means to secure sustained engagement. In: IEEE international symposium on robot and human interactive communication (ROMAN)
[5]. Lee J, Kiser J, Bobick A, Thomaz A (2011) Vision-based contingency detection. In: ACM/IEEE international conference on human-robot interaction (HRI)
[6]. Chao C, Lee J, Begum M, Thomaz A (2011) Simon plays Simon says: The timing of turn-taking in an imitation game. In: IEEE international symposium on robot and human interactive communication (ROMAN)
[7]. Sumioka H, Yoshikawa Y, Asada M (2010) Reproducing interaction contingency toward open-ended development of social actions: Case study on joint attention. In: IEEE transactions on autonomous mental development
[8]. Triesch J, Teuscher C, Deak G, Carlson E (2006) Gaze following: why (not) learn it? In: Developmental science
[9]. Butko N, Movellan J (2010) Infomax control of eye movements. In: IEEE transactions on autonomous mental development
[10]. Csibra G, Gergely G (2006) Social learning and social cognition: The case for pedagogy. In: Processes of changes in brain and cognitive development. attention and performance. Oxford University Press, London[18]. Gold K, Scassellati B (2006) Learning acceptable windows of contingency.In: Connection science
[11].Ashok Kumar R, Marimuthu K (2014) Prediction of stochastic cognitive neural schema with neural network paradigm of latent semantic nodes in autobot—humanoid robot using nonlinear regression of Gaussian sigmoidal curves in Boltzmann normali- sation. International Information Institute, Tokyo, Japan. Inf Int Interdiscip J 17(8):3971–3984
[12].Ashok Kumar Ramadoss , Investigation of Data Concurrency of Sensory fusion in Humanoid Robot, IJAMAE - International jounal of advancement inmechanical and aeronautical engineering,vol 1, pp 45-49, IRED, Institute ofResearch engineers and Doctors, NEW YORK,**USA**..ISBN: 978-981-07- 6261- 2doi:10.3850/ 978- 981-07-6261-2_61: ISSN: 2372-4153, 2013
[13].Ashok Kumar Ramadoss & Marimuthu Krishnaswamy , Embedding inference engine in fuzzy expert robotic system shell in a humanoid robot platform for selecting stochastic appropriate fuzzy implications for approximate reasoning, Artif Life Robotics, **Springer, SG Germany**, vol. 20, no. 1, pp. 13-18. ISSN:14335298, (ANNEXURE 2), Version 2013. 2. 1, 2015 doi.org**/10.1007/S10015-014-0189-2** https://link.springer.com/article/10.1007/s10015-014-0189-2
[14]. Ashok Kumar Ramadoss & Marimuthu Krishnaswamy, Cognitive Potential impact Minimization by Mitigating through the implementation of correction factor in the TED algorithm for the concurrency control in anticipation error during different movements in the Ramda Humanoid robot, International Journal of Digital content Technologies and its applications, Advanced Institute of Convergence Information Technology Research Center, **South Korea,** vol. 2, no. 4, pp. 16-21, ISSN :19759339 (ANNEXURE 2), Version 2. 1, 2015
[15].Ashok Kumar Ramadoss,Fuzzification using Approximation with Fuzzy to Extract Structure and Motion Environments in Dynamic Humanoid Robotic System from the Opted and Uncertainty by Quantization in non monotone neural networks, International Journal of Universal association of computers and electronics engineers IJUACEE,VOL 1, pp 5-9, Institute of Research Engineers and Doctors, **Switzerland** ISBN No. 978-1-63248-131-3, 2017
[16].Saffiotti, "The uses of fuzzy logic in autonomous robot navigation," J. Soft Comput.,vol. 1, no. 4, pp. 180–197, 1997.
[17]E. Tunstel, T. Lippincott, and M. Jamshidi,"Behavior hierarchy for autonomous mobile robots: Fuzzy behavior modulation and evolution," Int. J. Intell. Automat. Soft Comput.,vol. 3, no. 1, pp. 37–49, 1997.
[18].Uncertain Schema Matching Based on FuzzyDecision Making (WENG Nian-feng,DIAO Xing-chun and CAO Jian-jun) ,INFORMATION - An International Interdisciplinary Journal, International Information Institute, Tokyo, Japan, Vol.15,No.11(B), pp.5125-5136, Novemver, 2012.
[19].Watanabe N, Imaizume T (1993) A fuzzy statistical test of fuzzy hyphotheses. Fuzzy Sets Syst 5392:167–178
[20].Johannsen G (1972) Development and optimization of a non linear multiparameter human operator model. IEEE Trans Syst Man Cyber 2(4):494–504
[21].Costello RG (1968) The surge model of the well—trained human operator in simple manual control. IEEE Trrans Man Mach Syst MMS 9(1):2–9 11. Zhu A, Yang SX (2007) Neuro fuzzy - based approach to mobile robot navigation in unknown environments. IEEE Trans Syst Man Cybern C 37:610–621
[22] Bernreiter L, Ott L, Nieto J, Siegwart R, Cadena C (2021) Phaser: a robust and correspondence-free global pointcloud registration. IEEE Robot Autom Lett 6(2):855–862. https://doi.org/10.1109/LRA.2021.3052418
[23] Ansel J, Yang E, He H, Gimelshein N, Jain A, Voznesensky M, Bao B, Bell P, Berard D, Burovski E, Chauhan G, Chourdia A, Constable W, Desmaison A, DeVito Z, Ellison E, Feng W, Gong J, Gschwind M, Hirsh B, Huang S, Kalambarkar K, Kirsch L, Lazos M, Lezcano M, Liang Y, Liang J, Lu Y, Luk C, Maher B, Pan Y, Puhrsch C, Reso M, Saroufim M, Siraichi MY, Suk H, Suo M, Tillet P, Wang E, Wang X, Wen W, Zhang S, Zhao X, Zhou K, Zou R, Mathews A, Chanan G, Wu P, Chintala S (2024) PyTorch 2: faster machine learning through dynamic python bytecode transformation and graph compilation. In: 29th ACM international conference on architectural support for programming languages and operating systems, vol 2 (ASPLOS '24). ACM. https://doi.org/10.1145/3620665.3640366. https://pytorch.org/assets/pytorch2-2.pdf

[24] Tranzatto M, Dharmadhikari M, Bernreiter L, Camurri M, Khattak S, Mascarich F, Pfreundschuh P, Wisth D, Zimmermann S, Kulkarni M, Reijgwart V, Casseau B, Homberger T, De Petris P, Ott L, Tubby W, Waibel G, Nguyen H, Cadena C, Buchanan R, Wellhausen L, Khedekar N, Andersson O, Zhang L, Miki T, Dang T, Mattamala M, Montenegro M, Meyer K, Wu X, Briod A, Mueller M, Fallon M, Siegwart R, Hutter M, Alexis K (2022) Team CERBERUS wins the DARPA subterranean challenge: technical overview and lessons learned. arXiv. https://doi.org/10.48550/ARXIV.2207.04914. arXiv:2207.04914
[25] Tranzatto M, Miki T, Dharmadhikari M, Bernreiter L, Kulkarni M, Mascarich F, Andersson O, Khattak S, Hutter M, Siegwart R, Alexis K (2022) Cerberus in the darpa subterranean challenge. Sci Robot 7(66):9742. https://doi.org/10.1126/scirobotics.abp9742
[26] Yang H, Shi J, Carlone L (2021) Teaser: fast and certifiable point cloud registration. IEEE Trans Rob 37(2):314–333. https://doi.org/10.1109/TRO.2020.3033695
[27] Goodarzi R, Korayem MH, Tourajizadeh H, Nourizadeh M (2022) Nonlinear dynamic modeling of a mobile spatial cable-driven robot with flexible cables. Nonlinear Dyn 108(4):3219–3245
[28] Wang, JL., Song, JL., Liu, AR. *et al.* Correction to: Design and architecture of a slender and flexible underwater robot. *Intel Serv Robotics* **17**, 1189 (2024). https://doi.org/10.1007/s11370-024-00567-w
[29] Goodarzi R, Korayem MH, Tourajizadeh H, Nourizadeh M (2022) Nonlinear dynamic modeling of a mobile spatial cable-driven robot with flexible cables. Nonlinear Dyn 108(4):3219–3245
[30] Dahmane S-A et al (2023) Analysis and compensation of positioning errors of robotic systems by an interactive method. J Braz Soc Mech Sci Eng 45(2):119
[31] Tao W, Huang H (2023) Fast and robust training and deployment of deep reinforcement learning based navigation policy. In: 2023 IEEE international conference on unmanned systems (ICUS). IEEE, pp 1581–1586

About Author

Dr.Ashok Kumar Ramadoss, Associate Professor, EX-Scientist and Specialist (SIV Industries Ltd.,),Project LEADER (Society Generalle' Software Asia French MNC ITPL Bangalore and LG soft Korean MNC),

Senior Global Member Universal Association of Computers and Electronics Engineers, Sr.MUACEE (New York US- IRED).

Best Paper Award Winner in Humanoid Robotics at International Conference - KL, Malaysia.

Appreciation Award received at International conference in Neural Schema for Humanoid Robotics in Computing ,Communication and Information Technology @ ZURICH, SWITZERLAND.

Invited Speaker on "Recent Cognitive trends and Activities on Humanoid Robots" @ TOKYO, JAPAN,Editorial

Board Member in journal "Technoarete Transactions on Industrial Robotics and Automation Systems"

International Scientific and Technical Committee Member and Editorial Board Member in Information and Communication Engineering Committee, for International conferences and journals in World Academy of Science, Engineering and Technology, having i10-index:1775, headquarters at London UK.,International

Advisory Board Member Scope Database.

Senior member in the HONG KONG Society of Robotics and Automation (HKSRA),He is the Member in SRS Robotics surgery Illinois, USA and Orlando Florida

Author is the best paper award winner at Bangkok, Thailand on 2024 in an International Conference on Information Technology and Management in Humanoid Robotics.