Modular Framework Kinematic and Fuzzy Reward Reinforcement Learning Analysis of a Radially Symmetric Six-Legged Robot

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Abstract: Hexapod Robots gives us the ability to study walking robots without facing problems such as stability in many aspects. It has a great deal of flexibility in movement even if a leg becomes malfunctioned. Radially symmetric (hexagonal) hexapods have more flexibility in movement than rectangular leg alignments. Because of symmetry they can move in any direction and time efficiently. Inverse kinematic problem of this kind of hexapods is solved through a modular mobile view considering six degrees of freedom for the trunk. Then typical tripod and wave gaits are analyzed and simulated through the presented formulation. In Reinforcement Learning algorithm for walking it is important how to make reward signal with respect to robot's actions and states. A fuzzy approach is presented and analyzed to generate reward signals. It is shown that the presented fuzzy system generates more considerable accurate rewards with better performance than functional rewards which are used in walking learning problems.

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1. Introduction

Multi Legged robot locomotion has been such a keen interest over the years to the researchers due to their advantages of the superior mobility in irregular terrain and less hazardous influences on environment comparing with the wheeled robots. A multi-legged robot possesses a tremendous potential for maneuverability over rough terrain, particularly in comparison to conventional wheeled or tracked mobile robot. It introduces more flexibility and terrain adaptability at the cost of low speed and increased control complexity [1]. The kinematic properties of a six- legged robot can significantly influence locomotion procedure. A Hexapod motion analysis is a complex combination of kinematic chains. Open chains when legs are in swing phase and closed chains when in stance phase with the trunk body. Lilly and Orin [2] treats a walking robot as a multiple manipulators (i.e. legs) contacting an object, which is the trunk body. Wang and Din [3] analyzed a radially symmetric hexapod kinematic and gait analysis through a manipulation view by finding closed loops assuming the trunk is parallel to the ground and they did not considered tilt of the trunk so only 3 degrees of freedom were considered for the robot's body. Shah, Saha and Dutt [4] modeled legged robots as combination of floating-base three-type systems as kinematic modules where each is a set of serially connected links only. They used this idea for kinematic analysis of a biped and quadruped robots. In this paper modular framework approach is used for solving inverse kinematic problem of a radially symmetric six-legged robot. In this kind of hexapod robot each leg has a different coordinate frame orientation compared to the other legs unlike rectangular hexapods which two set of legs are oriented as two parallel sets on sides of the trunk. Therefore, gait analysis and legs behavior of these two different hexapod designs are different from each other. A mobile view is proposed here to solve the inverse kinematic problem of a six-legged robot assuming that the trunk has its 6 degrees of freedom. After solving the inverse kinematic problem, trajectory of each leg for gait analysis is the main problem to how to perform a swing step. For smooth walking, a swing cosine function [5][6] is analyzed and simulated for tripod and wave gait.

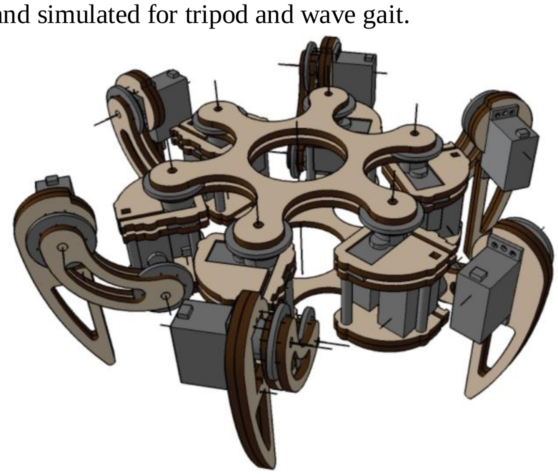

Fig 1. 18 DoF SKPRbot six-legged walking robot design

Control of legged robots is difficult, requiring fairly heavy on-line computations to be performed in real time. Hence a machine-learning solution is needed [7]. One machine-learning method for legged robots, which has great potential, is Reinforcement Learning (RL). RL is a promising approach to achieve the control of complex robots in dynamic environments; Josep M. Porta had developed a Robotic Oriented Reinforcement Learning [8]. This approach helps with the basic learning platform for problem with walking learning. A simple RL approach is used to develop walking gaits for hexapod [9][10]. Matt R. Bunting has implemented Q-learning [17] (a form of RL) on a hexapod [12] and has shown the capability of this algorithm for walking control. One of the strengths of Q-learning is that it is able to compare the expected utility of the available actions without requiring a model of the environment. In RL techniques one of the challenges is how to reward the actions in different states. There are different approaches and researches for rewarding regarding different systems and purposes. Accuracy and computation time are two parameters which should considered in this content. A fuzzy inference system is presented in this paper for giving the proper reward signal to the robot in walking learning problem.

In the first section the kinematic analysis of the robot is done using a modular framework view approach with the complete Degrees of Freedom (DoF) of the robot's trunk. After formulating the kinematics of the hexapod robot typical wave and tripod gaits are implemented on the presented kinematic model. In the final section the RL Problem in a hexapod robot is defined and the rewarding is discussed using a fuzzy system.

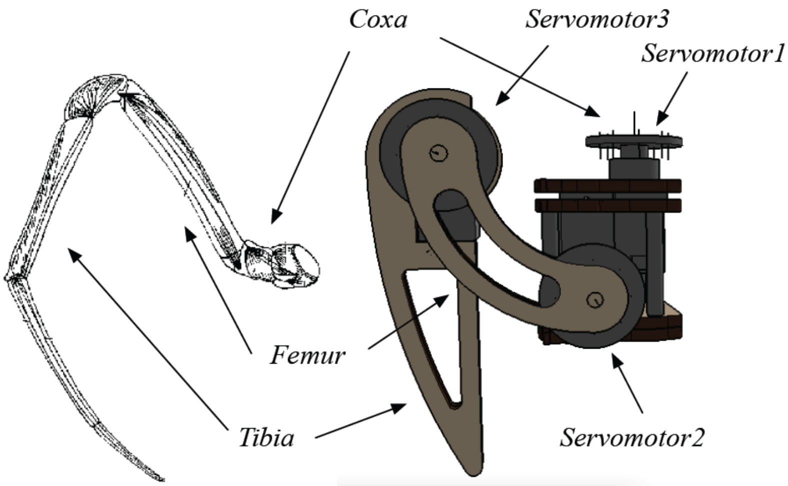

Fig 2. The hexapod's leg design inspired by insects

2. Kinematic Analysis

The hexapod prototype design which is studied on this paper is a 18 DoF robot with 3 DoF for each leg. It is a Google SKPRbot design, a biologically inspired design based on spider's anatomy. Each leg has three servomotors, which are modeled as 3 revolute joints as shown in figure 2.

2.1. Inverse Kinematic of Hexagonal Hexapod Robot

In locomotion analysis the problem is to find out how to assign the joint variables to move in the desired way, i.e. to find joint variables in terms of trunk configuration. First of all the architecture of the robot is simplified in 7 modules, a hexagon trunk and 6 limbs between the trunk and ground as shown in figure 3.

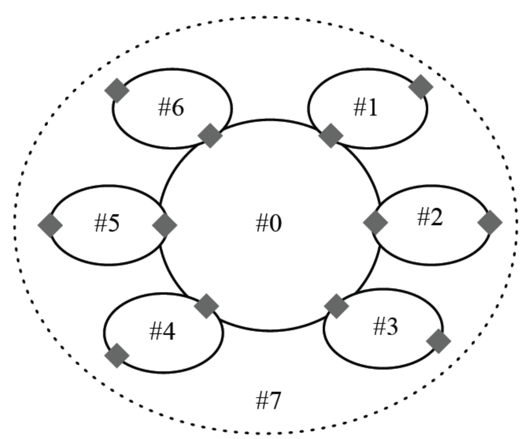

Fig 3. The modular view of hexapod robot. The robot on the ground is divided into 8 groups of kinematic chains. The squares show the contact between the groups.

Two coordinate frames are assigned. First is $\{O\}$ on the ground, and the second one is the trunk, $\{O^{'}\}$. 6 degrees of freedom is considered for the trunk as shown in figure 4, 3 are translational movement in $x^{'}$, $y^{'}$ and $z^{'}$ direction and 3 are rotational movement around $x^{'}$, $y^{'}$ and $z^{'}$ which are roll, pitch and yaw respectively. Forward motion is considered as in the direction of $x^{'}$.

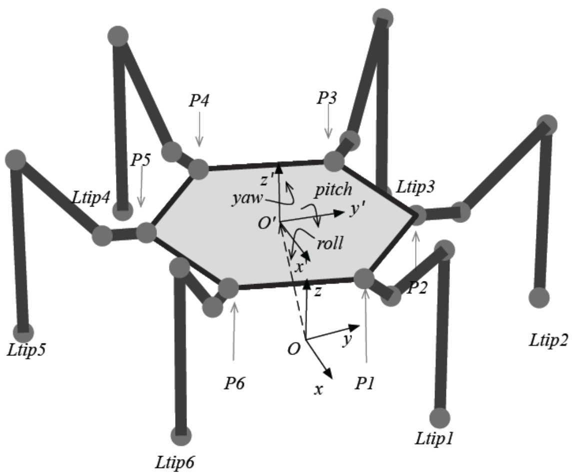

Fig 4. Hexagonal hexapod coordinate frame assignment, ground frame $\{\boldsymbol{O}\}$ and trunk frame $\{\boldsymbol{O}^{'}\}$

The main idea for solving inverse kinematic of this robot came from a modular view of floating trunk and serial kinematic chains [4]. To obtain the kinematic chain and find out the joint variables we define a homogeneous transformation matrix to transform the Legs' tips from ground coordinate frame to trunk coordinate frame. This transformation matrix can be written as (1).

$$ {}_{O}^{O'}T = \begin{bmatrix} R_z(\theta_z)R_y(\theta_y)R_x(\theta_x) & -OO' \\ 0 & 1 \end{bmatrix} \quad (1)$$

R_z, R_y and R_x are rotational transformation matrices around z, y and x respectively and $OO^{'}$ is the distance from $O^{'}$ to O. In coordinate frame $\{O^{'}\}$, $P_1..P_i..P_6$ are the corners of the trunk's hexagon and are always constant in $\{O^{'}\}$. $L_{tip_1}..\ L_{tip_i}..L_{tip_6}$ are legs' tips position in $\{O\}$. The legs' tips positions can be transferred from $\{O\}$ to $\{O^{'}\}$ using defined transformation matrix in (1).

$$L_{tip_i}{}' = {}_{O}^{O'}T L_{tip_i} \quad (2)$$

$$L_{tip_i} = \begin{bmatrix} x_{tip_i} \\ y_{tip_i} \\ z_{tip_i} \end{bmatrix} \quad (3)$$

And now in $\{O^{'}\}$ the inverse kinematic can be solved for each leg.

$$\begin{bmatrix} x_{lt_i} \\ y_{lt_i} \\ z_{lt_i} \end{bmatrix} = L_{tip_i}{}' - P_i \quad (4)$$

$$P_i = \begin{bmatrix} P_{ix} \\ P_{iy} \\ P_{iz} \end{bmatrix} \quad (5)$$

$$\begin{aligned} x_{lt_i} = \; & x_{tip_i} cos\theta_y cos\theta_z \\ & + y_{tip_i}(cos\theta_x sin\theta_z \\ & \qquad + cos\theta_z sin\theta_y sin\theta_x) \\ & + z_{tip_i}(sin\theta_x sin\theta_z \\ & \qquad - cos\theta_x cos\theta_z sin\theta_y) \\ & - OO'_x + P_{ix} \end{aligned} \quad (6)$$

$$\begin{aligned} y_{lt_i} = \; & -x_{tip_i} cos\theta_y sin\theta_z \\ & + y_{tip_i}(cos\theta_x cos\theta_z \\ & \qquad - sin\theta_y sin\theta_x sin\theta_z) \\ & + z_{tip_i}(cos\theta_z sin\theta_x \\ & \qquad + cos\theta_x sin\theta_y sin\theta_z) \\ & - OO'_y - P_{iy} \end{aligned} \quad (7)$$

$$\begin{aligned} z_{lt_i} = \; & x_{tip_i} sin\theta_y - y_{tip_i} cos\theta_y sin\theta_x \\ & + z_{tip_i} cos\theta_y cos\theta_x - OO'_z - P_{iz} \end{aligned} \quad (8)$$

2.2. Forward and Inverse Kinematic Analysis of one leg

Each leg can be seen as a serial manipulator where its base is fixed on the trunk and its end point is on the ground or on its swing path. For forward kinematic analysis using Denavit-Hartenberg (DH) parameters of one leg [5] The transformation matrix of each joint can be written based on frames shown in figure 5.a and table 1. Three joints and five frames are defined from the initialized frame to the end point of the leg.

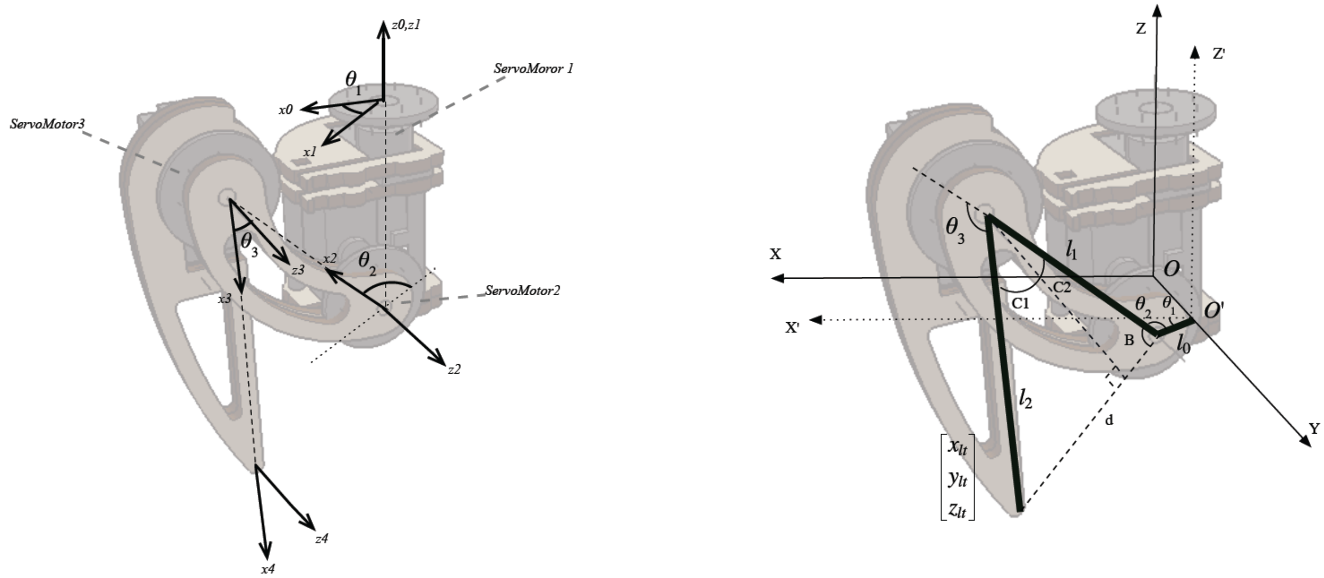

Fig 5. Hexapod's leg link frame assignment for kinematic analysis. The left figure show Link-frame assignments based on Denavit Harten-berg parameters. The right figure is a 3 DoF hexapod leg design link assignment and parameters for inverse kinematic analysis.

1. Denavit-Hartenberg parameters of a 3 DoF hexapod's leg

Link	α_{i-1}	a_{i-1}	d_i	θ_i
1	0	0	0	θ_1
2	$-\pi/2$	l_0	0	θ_2
3	0	l_1	0	θ_3
4	0	l_2	0	0

The homogeneous transformation matrices of leg's links based on DH parameters in table 1 are presented in (9).

$$ {}_4^0T_i = \begin{bmatrix} c_{12_i}c_{1_i} & -s_{12_i}c_{1_i} & -s_{1_i} & c_{1_i}(l_0 + l_1c_{2_i} + l_{2_i}c_{23_i})(9) \\ c_{12_i}s_{1_i} & -s_{12_i}s_{1_i} & c_{1_i} & s_{1_i}(l_0 + l_1c_{2_i} + l_2c_{23_i})(10) \\ -s_{23_i} & -c_{23_i} & 0 & -l_1s_{2_i} + l_2s_{23_i}(11) \\ 0 & 0 & 0 & 1(12) \end{bmatrix} \quad (9) $$

where c_1 , c_{12} , c_{23}, s_1 , s_{12} and s_{23} stands for $cos\theta_1$, $cos(\theta_1+\theta_2)$, $cos(\theta_2+\theta_3)$, $sin\theta_1$, $sin(\theta_1+\theta_2)$ and $sin(\theta_2+\theta_3)$ respectively. ${}_4^0T_i$ transforms from end point which is the ith leg's tip to the base coordinate frame. The position of the leg tip in $x'y'z'$ coordinate frame can be found using homogeneous transformation matrix from base coordinate frame to endpoint coordinate frame. Figure 5.b shows the parameters and link assignments for inverse kinematic analysis of one leg. The reason that O' is defined adjacent to O is the vertical distance between the shaft of servomotors number 1 and 2.

$$ \begin{bmatrix} x_{lt_i} \\ y_{lt_i} \\ z_{lt_i} \\ 1 \end{bmatrix} = {}_4^0T \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \quad (10) $$

$$ x_{lt_i} = c_{1_i}(l_0 + l_1c_{2_i} + l_2c_{23_i}) \quad (11) $$

$$ y_{lt_i} = s_{1_i}(l_0 + l_1c_{2_i} + l_2c_{23_i}) \quad (12) $$

$$ z_{lt_i} = -l_1s_{2_i} + l_2s_{23_i} \quad (13) $$

where x_{lt_i} , y_{lt_i} and z_{lt_i} are ith leg tip position in $\{O'\}$ and θ_1, θ_2 and θ_3 are joint angels which has been shown in figure 5.b. Inverse kinematic equations for one leg can be written as:

$$ \theta_{1i} = atan2(y_{lt_i}, x_{lt_i}) \quad (14) $$

$$ d_i = \sqrt{(x_{lt_i} - l_0c_1)^2 + (y_{lt_i} - l_0s_1)^2 + z_{lt_i}^2} \quad (15) $$

$$ B_i = acos(\frac{d_i^2 + l_1^2 - l_2^2}{2l_1d_i}) \quad (16) $$

$$ \theta_{2i} = asin(\frac{-z_{lt_i}}{d_i}) - B_i \quad (17) $$

$$ C1_i = acos(\frac{l_1sinB_i}{l_2}) \quad (18) $$

$$ C2_i = \frac{\pi}{2} - B_i \quad (19) $$

$$ \theta_{3i} = \pi - C1_i - C2_i \quad (20) $$

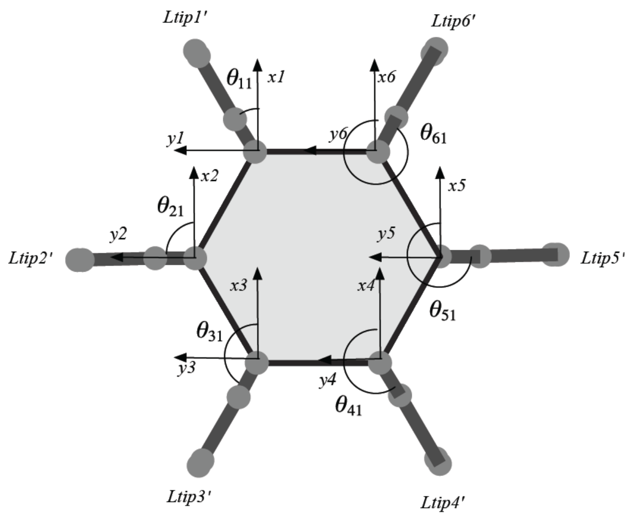

Fig 6. Legs frame assignments on hexapod's main body

3. Gait Analysis

Six legs are moving with different time sequences together to form a walking gait. Every walking gait can be simplified to some similar rules for every leg namely step. By applying these algorithms to each leg walking can be achieved. In gait analysis leg task can be classified as two phases, stance and transfer (swing) phase. When the robot is moving on desired trajectory i.e, $P_x(t)$, $P_y(t)$, $P_z(t)$, $\theta_x(t)$, $\theta_y(t)$ and $\theta_z(t)$ some legs on the ground are pushing to move the trunk in desired direction and orientation while the other legs are getting into new position. To solve this trajectory using leg tips on the ground as through (6) to (8) and (14) to (20) inverse kinematic in each step can be found.

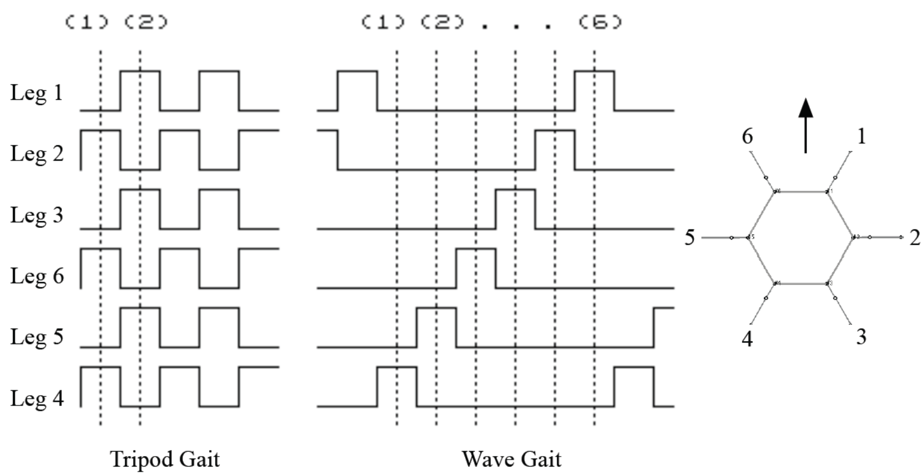

Fig 7. Tripod gait and wave gait transfer phase timings.

While the robot is moving some legs are swinging forward to get into the new position for the next step. It is important for leg not to impact the ground; the velocity at the start and end of swing phase should be zero. Also actuation control signals should be smooth. Therefore a proper trajectory should be defined for $i \in (swinglegs)$[5,6].

$$x_{tip_i} = 2\dot{P}_x \delta t_{step} \left(1 - cos\left(\frac{\pi t}{\delta t_{step}}\right)\right) \quad (21)$$

$$y_{tip_i} = 2\dot{P}_y \delta t_{step} \left(1 - cos\left(\frac{\pi t}{\delta t_{step}}\right)\right) \quad (22)$$

$$z_{tip_i} = h\left(1 - cos\left(\frac{2\pi t}{\delta t_{step}}\right)\right) \quad (23)$$

$\dot{P}_x$ and $\dot{P}_y$ are speed of robot's trunk in *x* and *y* directions, *h* is the height of each step in swing phase and δt_{step} is the time duration of each step.

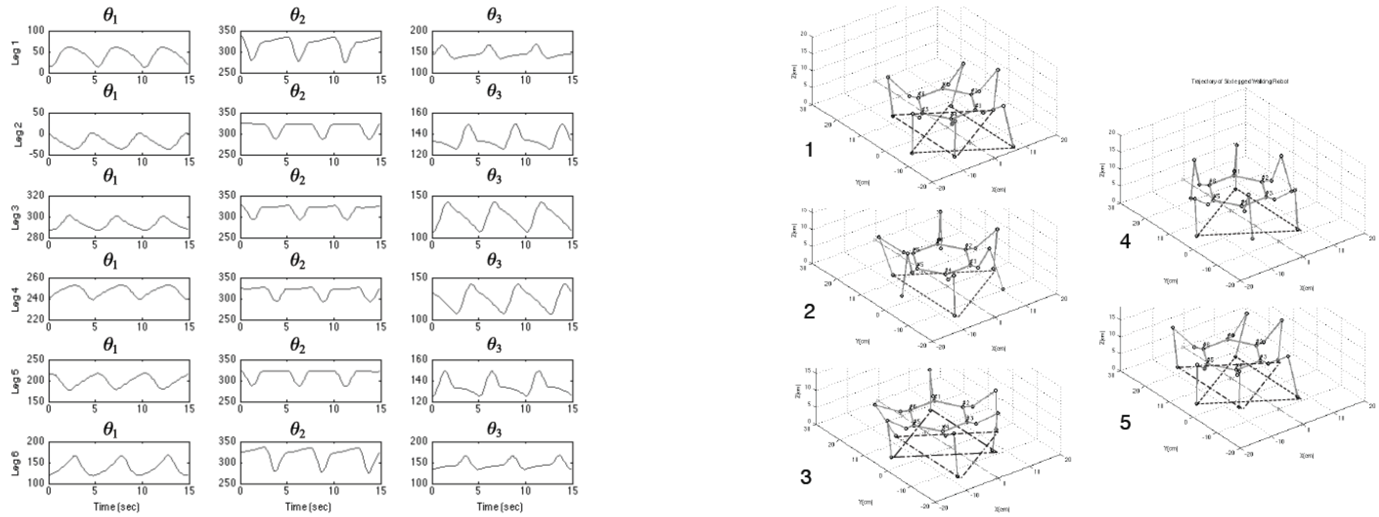

Fig 8. Simulation results of tripod gait analysis using discussed kinematic formulation. Joint space variables of hexapod robot in tripod gait through one complete step (left) and Tripod walking gait simulated in one step. Triangles are supported legs in stance phase (right).

Two walking gaits, wave and tripod gait have been studied and simulated using presented formulation [14]. In tripod gait for example two equilateral triangles are defined, one for standing legs and one for another swinging legs. The standing legs are on the ground and form a triangle. When the robot is going forward on standing legs the other triangle (the other three legs' tip forms) is moving forward above the ground to get into new position, i.e. swing phase as shown in figure 7. The results of inverse kinematic for tripod gait are shown in figure 8.

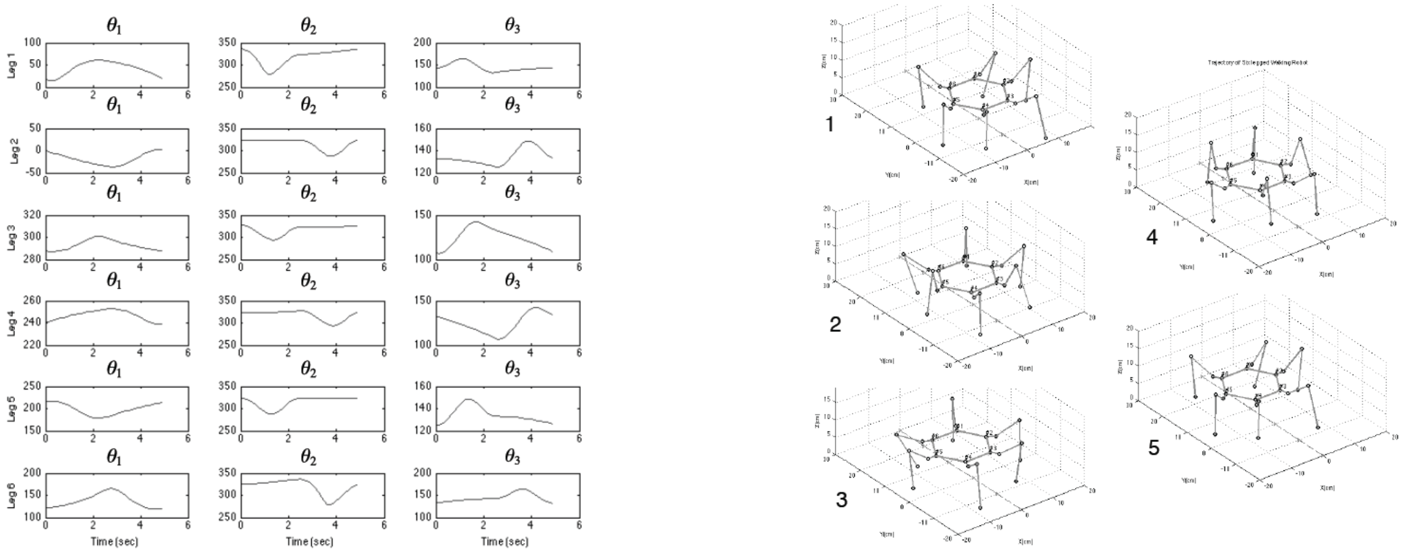

Fig 9. Simulation results of wave gait analysis using discussed kinematic formulation. Joint space variables of hexapod robot in wave gait through one complete step (left) and wave walking gait simulated in one step (right).

In wave gait robot moves its legs one by one to get the highest stability margin but so slower, as shown in figure 7. Results and simulation are in figure 9.

4. Fuzzy Reward in Reinforcement Learning Problem of Walking

Reinforcement Learning (RL) techniques are interesting subjects in both control theory and cognitive sciences. In control theory, building a system that works completely perfect is quite difficult, and it is an exhaustive procedure when unexpected errors or disturbances affect the system. By building a system that learns how to accomplish a task on its own, there becomes no need to calculate and predict complex control algorithms. In cognitive sciences, the ability to learn is a core component of cognition. Reinforcement learning algorithm is one such simple learning algorithm. This section explores the ability of a robotic hexapod agent to learn how to walk, using only the ability to move its legs and tell whether if the robot is moving forward. Therefore, the hexapod may be seen as an analog for a biological subject lacking all but the basic instincts observed in infants and having no external support or parental figure to learn from. The main challenging problem in this content is to establish the interaction between the environment and the six-legged robot. A system that would tell the robot how good is its movement or its actions. A typical way is using a mathematical function whichuses sensory data and tells how good or bad an action is in a certain state [17].

$$R(s,a) = \frac{forward}{\sqrt{translation^2 + tilt^2}} \tag{24}$$

Another approach which is presented and discussed here is a fuzzy inference system that uses sensory data and tells the reward value. The design of this system is shown in figure 10.

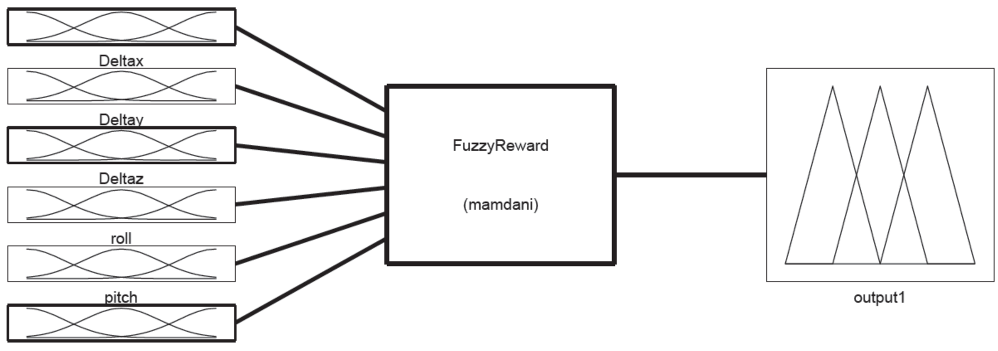

Fig 10. The diagram of fuzzy system which is used to generate reward values using sensors data (with respect to actions and states).

Sensory data comes from 3-axis digital compass, 3-axis digital gyroscope and 3-axis digital accelerometer. Using these three sensors displacement and tilting can be found approximately using two integrators. 6 inputs to the Fuzzy Inference System (FIS) are displacements in *x*, *y* and *z* direction and tilt around *x*, *y*, and *z*.

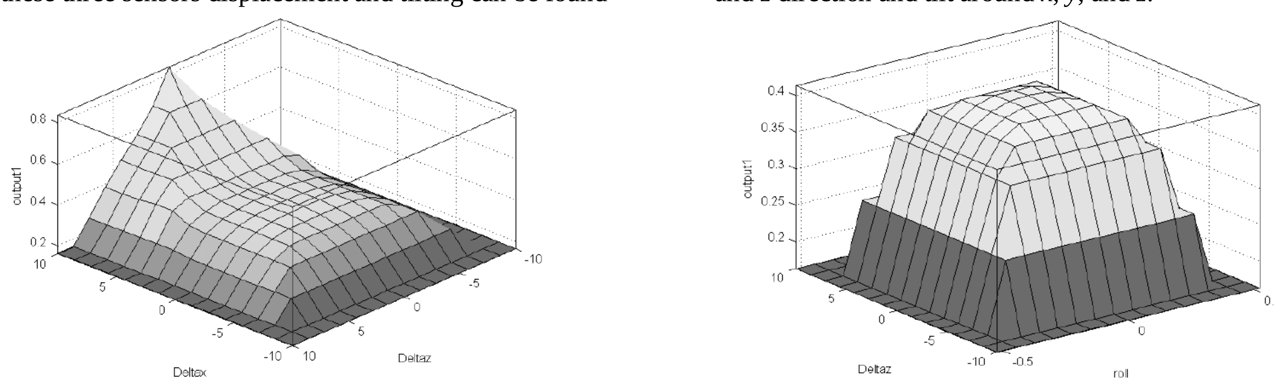

Fig 11. The surface of fuzzy system with respect to different inputs. Due to inputs characteristics similarity excluding Δ_x which is shown in right figure for example, the other surfaces will be the same as these two surfaces.

It is assumed that moving in *x* direction is forward movement and is the desired and the other 5 inputs denotes the parameters in other directions and movements which are undesired variables. So the surfaces of FIS are shown in figure 11. The surfaces of Δ_x to other 3 variables also would be the same because of the definition of inputs. The simulation compares the defined FIS reward and mathematical reward in different states is shown in figure 11. It is should mentioned that an offset and gain is applied to fuzzy reward signal for better comparison understanding.

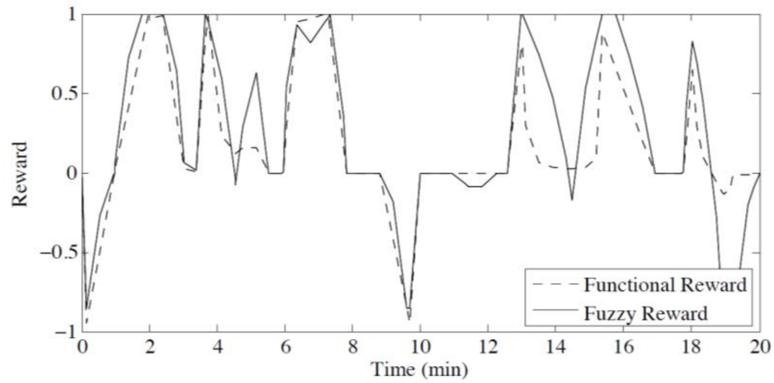

Fig 12. Signals of both functional reward which is mathematical formula and fuzzy reward. As shown fuzzy reward signal is more detailed and accurate.

As the results show the fuzzy reward makes more sense and have more useful information compared to mathematical reward function. However the average calculation time is measured and it has been seen fuzzy reward requires more time for computation. The average evaluation time for fuzzy reward in simulation is around 2 *msec* but for mathematical one is 50 *µsec*. Evaluation time is so important in real-time control.

There are some approaches which reduces the number of calculations and complexity of fuzzy systems. One efficient way is to reduce number of inputs which have similar properties or have been controlled with similar rules. A new variable combined of variables with similar rule base is defined as (25) to reduce the number of calculations.

$$\Lambda = \sqrt{\Delta_y^2 + \Delta_z^2 + \theta_x^2 + \theta_y^2 + \theta_z^2} \tag{25}$$

where Λ denotes the tilt and translation. Therefore, Λ FIS with Λ and Δ_x as 2 inputs and reward as output can be defined. The new FIS structure is shown in 13.

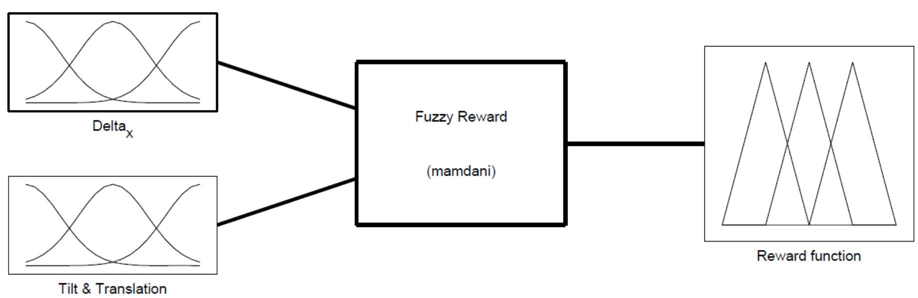

Fig 13. The diagram of Λ fuzzy reward.

And the rules surface is defined as before but with new variables the rules are decreased and the rules surface of the Λ FIS is shown in figure 14.

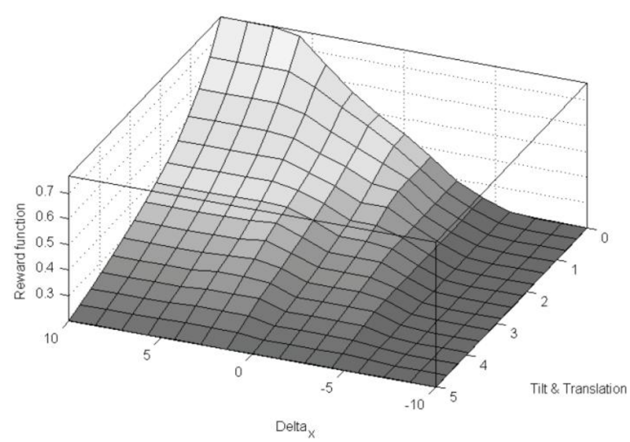

Fig 14. The surface of Λ fuzzy reward with respect to Δ_x & Λ.

The comparison shown in the figure 15 denotes that the efficiency of the FIS decreased slightly but compared to the mathematical reward function Λ FIS is more accurate. Also the evaluation time decreased to less than half of single evaluation in 6-input FIS. Mathematical reward is not as accurate as FIS systems but evaluates data at higher speed. Time is a big deal in real time control and online processing. Fuzzy reward gives more accurate and detailed reward data. Although it is obvious that aggregation of inputs can speed up the FIS, it should be assured that there would not be much loss of data during input aggregation. In this case as it is shown data loss did not happen and the Λ Fuzzy reward works as accurate as the normal 6-input Fuzzy reward design but at higher speed.

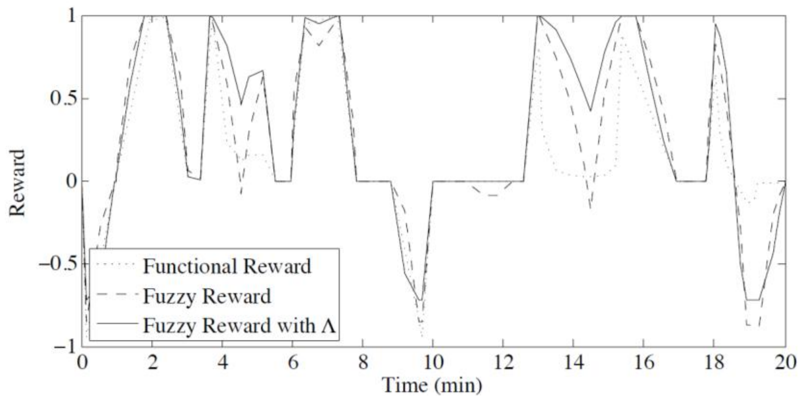

Fig 15. Comparison of reward evaluation of Λ fuzzy reward, the normal fuzzy reward and funtional reward. It is shown that Λ fuzzy reward is slightly less accurate as the normal fuzzy reward.

2. Speed performance comparison of different Rewarding systems

Reward	Time required for 1000 evaluations	Average time for single evaluation
Functional Reward	0.043 *sec*	0.043 *ms*
Fuzzy Reward	1.834 *sec*	1.834 *ms*
Fuzzy Reward with Λ	0.072 *sec*	0.72 *ms*

5. Conclusion

Kinematic formulation of a radially symmetric (hexagonal) hexapod has been studied in this paper. Trajectory of two typical gaits are solved through the formulation and simulated considering smooth actuation signals. It is shown that a modular view for solving inverse kinematic problem for this kind of robot simplifies the complexity of different orientation of legs and gait analysis can be implemented as other robots with a general algorithm to each leg despite the orientation of its legs coordinate frames. In Reinforcement Learning for walking the reward signal is generated using Fuzzy Inference System and the comparison of the results with mathematical reward has shown that fuzzy reward gives more accurate data with slower computation compared to mathematical one. A new approach for reducing computation time in fuzzy system is applied and results have shown that the presented system works faster with the same accuracy. Therefore, the performance of the fuzzy reward has been improved.

References

1. S.M. Song and K.J.Waldron, Machines That Walk: The Adaptive Suspension Vehicle, The MIT Press, Cambridge, Massachusetts, 1989.W. K. Chen, Linear Networks and Systems (Book style). Belmont, CA: Wadsworth, pp. 123-135,1993.
2. K. W. Lilland D.E Orin, Efficient dynamic simulation of multiple chain robotic systems • , *Proc of the 3rd Annual Conf, on Aerospace Conputational Control*, pp. 73-87, Aug 1989.
3. Z. Wang, X. Ding, A. Rovetta and A. Giusti, Mobility analysis of the typical gait of a radial symmetrical six-legged robot • , *Mechatronics* 21, pp. 1133-1146, 2011.
4. S.V. Shah, S.K. Saha and J.K. Dutt, Modular framework for dynamic modeling and analyses of legged robots • , *Mechanism and Machine Theory* 49, pp. 234-255, 2012.
5. M.C. GarcaLpez, E.Gorrostieta-Hurtado, E. Vargas-Soto, J.M. Ramos-ArreguÃ-n, A.

Sotomayor-Olmedo and J.C. Moya Morales, Kinematic analysis for trajectory generation in one leg of a hexapod robot • , *Procedia Technology*, Volume 3, pp. 342-350, 2012.

6. G. Figliolini, S.D. Stan and P. Rea, Motion Analysis of the Leg Tip of a Six-Legged Walking Robot • , *Proceedings of the 12th IFToMM World Congress*, Besanon (France). 2007.
7. A. Preumont, An investigation of the kinematic control of a six-legged walking robot • , *Mechatronics*, Volume 4, Issue 8, pp. 821-829, December 1994.
8. R. Vidoni, A. Gasparetto, Efficient force distribution and leg posture for a bio-inspired spider robot • , *Robotics and Autonomous Systems*, Volume 59, Issue 2, pp. 142-150, February 2011.
9. D. E. Koditschek, R. J. Full, M. Buehler, Mechanical aspects of legged locomotion control • , *Arthropod Structure* amp; Development, Volume 33, Issue 3, pp. 251-272, 1 July 2004.
10. J. Estremera, J.A. Cobano, P. Gonzalez de Santos, Continuous free-crab gaits for hexapod robots on a natural terrain with forbidden zones: An application to humanitarian demining • , *Robotics and Autonomous Systems*, Volume 58, Issue 5, pp. 700-711, 31 May 2010.
11. M.Sorin, Ni.Mircea,Basic Walking Simulations And Gravitational Stability Analysis For A Hexapod Robot Using Matlab • , *Annals Of The University Of Craiovavolume*, 8(35) No. 1, pp. 44-55, 2011.
12. A. Roennau, T. Kerscher, and R. Dillmann, Design and kinematics of a biologically-inspired leg for a six-legged walking machine, • 3rd IEEE RAS and EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob '10), pp. 626-631, September 2010.
13. M.R. Fielding, G.R. Dunlop, Omnidirectional Hexapod Walking and Efficient Gaits Using Restrictedness,*The International Journal of Robotics Researchvol*, 23 no. 10-11, October 2004.
14. M. Ahmed, M. Raisuddin Khan, M.Billah, and S. Farhana, • Multi-agent Application: A Novel Algorithm for Hexapod Robots Gait Transitions • , *Australian Journal of Basic and Applied Sciences*, 4(8), pp. 2292-2299, 2010.
15. Y. Ota, Y. Inagaki, K.Yoneda, S. Hirose, Research on a six-legged walking robot with parallel mechanism • ,*Intelligent Robots and Systems, 1998. Proceedings,IEEE/RSJ International Conference*, 13-17 Oct 1998.
16. U. Asif1 and J. Iqbal1, • A Comparative Study of Biologically Inspired Walking Gaits through Waypoint Navigation • , *Advances in Mechanical Engineering* Vol. 2011, Article ID 737403, 9 pages, 2011.
17. M.R.Bunting,Q-LearningHexapod • ,FinalProjectReport,ECE596C,CognitiveRobotics,2009.
18. J.P. Barreto, A.Trigo, P.Menezes, J. Dias, A.T.De Almeida, FED-the free body diagram method. Kinematic and dynamic modeling of a six leg robot • ,*Advanced Motion Control, 1998. AMC '98-Coimbra., 5th International Workshop*, Jul 1998.
19. U.Asif and J.Iqbal, An Approach to Stable Walking over Uneven Terrain Using a Reflex-Based Adaptive Gait, • *Journal of Control Science and Engineering*, vol. 2011, Article ID 783741, 12 pages, 2011.
20. D. Belter, K. Walas, A. Kasinski, Distributed control system of DC servomotors for six legged walking robot • ,*EPE PEMC - 13th International Power Electronics and Motion Control Conference, Poznan, Poland*, September 1-3, pp. 1044 -1049,2008.
21. D. Xingji. Weihai. Shouqian • Tripod gaits planning and kinematics analysis of a hexapod robot • , *International Conference on Control and Automation ChristchurchNew Zealand. IEEE*, pp. 1850-1855, 2009.

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