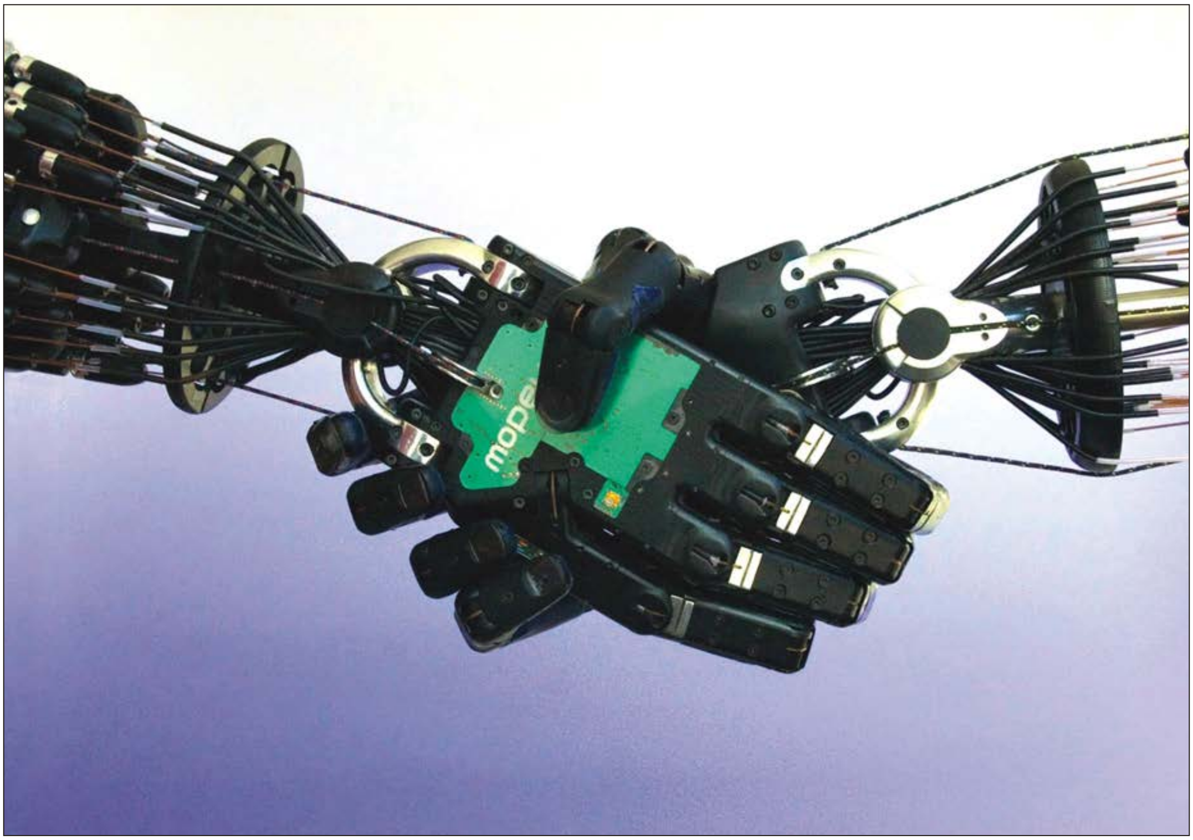

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An FCM-based Design for Balancing of Legged Robots

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ABSTRACT

Robot balancing is a challenging task when it comes to legged platforms, e.g., hexapods and quadrupeds. Fuzzy cognitive map (FCM) is well established as a decision making mechanism with many applications. This study presents the very first application of FCM-based inference for autonomous balancing in standard legged robots with 3-revolute joints, i.e., three degrees of freedom (DoF) per limb. FCM has been utilized for balancing control and placement of feet instead of solving complex Jacobians.

Key words: Fuzzy inference, legged robots, balancing control

INTRODUCTION

Fuzzy cognitive map (FCM) (Kosko, 1996) is a graph-like inference mechanism based on fuzzy logic and recurrent neural network methodologies. It consists of nodes and edges (causal links) whereby nodes influence each other depend on weights of edges or causal links. A node however is either a factor (input), or a decision indication (output), at any time instance. A set of graph edges (matrix) which exists among nodes, plays the key role in inference: deriving outputs from inputs. There are many approaches to train FCMs mostly by tuning their matrices including genetic algorithms (GA) (Stach *et al*., 2005; Ghazanfari *et al*., 2007) and Hebbian algorithms (Papageorgiou *et al*., 2006; Papageorgiou and Groumpos, 2005). However, regardless of the employed training technique, the main role of FCM is in inference.

In definition formula (Eq. 1) (Kosko, 1996), the new weight of each concept c_j at cycle (k+1) is defined from squashing the total effect of all concepts (c_1... c_n) on c_j into a standard range of (0, 1) using a logistic function symmetrically around 0.5 (sigmoid curve). Other threshold functions such as *tanh* can be used too (Papageorgiou and Groumpos, 2005). The total effect is in fact a sum of multiplications of each concept's weight (c_i) from the preceding cycle (k) by the weight of the respective causal link ($e_{i,j}$) which connects c_i to c_j (Ghazanfari *et al*., 2007). This is the main concept of FCM-based inference in nearly all methods.

$$c_j^{(k+1)} = \left(1 + e - \sum_{i=1}^{n} c_i^{(k)} e_{i,j}\right)^{-1} \text{ and } \ j \in \{1, ..., n\} \tag{1}$$

Motlagh *et al*. (2010), presented a new formulation of FCM where continuous decision productions need to be generated for successive actions where an action, e.g., resulted from ith decision instance, influences the next decision making behavior at instance (i+1)th. Instead of normalizing weighs around a fixed value as in "definition" and "incremental models" (Kosko, 1996), each concept's weight (at cycle k+1) is squashed about its previous weight (from cycle k) (Eq. 2)

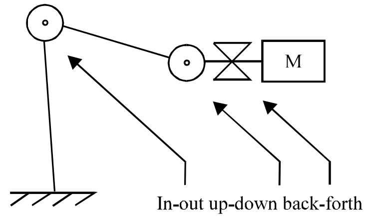

Fig. 1: Universal RRR joint configuration for 3-DoF Yaw, Pitch, Roll (YPR)

allowing for direct impact of initial weights on ultimate outputs, i.e., each weight determines the centre of the respective logistic function along successive cycles. This process facilitates continuous chain of actions which lead to accomplishment of a task, e.g., taking one forward step on the ground.

$$c_j^{(k+1)} = f\left(\sum_{i=1}^{n} c_i^{(k)} e_{i,j}\right)^{-1} \text{ and } f_{(x)} = \frac{\gamma c_j^{(k)} e^{\lambda x}}{\gamma c_j^{(k)} (e^{\lambda x} - 1) + 1} \tag{2}$$

and:

$$j \in \{1 \ldots n\},\ o < \gamma < 1$$

The developed model was successfully applied to modeling walking gait of quadrupeds in a simple way. As an extension to the previous work in Motlagh *et al.* (2010), this study is dedicated to modeling self-balancing behaviors of a 12 DoF quadruped, i.e., 3-DoF per limb which could be further elaborated for all kinds of legged platforms, like hexapods, etc. The joints configuration follows reptiles with the body suspending among limbs and each limb following RRR in Yaw (back-forth), Pitch (up-down), Roll (in-out) order as shown in the Denavit-Hartenberg diagram (Fig. 1).

The developed model: The method consists of (1) selection of FCM nodes which encompass all concepts related to the robot to be controlled (2) development of FCM edges in terms of direction and intensity through expert-defined assignment of causality relationships among node (3) running the model in real-time on a simulated quadruped platform (4) obtaining qualitative results in simulation as well as quantitative analysis of results to determine repeatability and robustness. Accordingly, Fig. 2 shows the developed FCM. Each graph edge or causal link connects an affecting input to an affected output or to another dependent input. Positive and negative links are shown with and, respectively.

It must be noted that the FCM is merely related to self-balancing features of the robot as intended in this article. However, the simulation and results are based on a more complex FCM which also includes kinematical factors, e.g., walk cycle as described by Motlagh *et al.* (2010) and dynamical factors, e.g., feet slippage. The 38 concepts assigned to the graph nodes define the entire factors related to robot balancing against any of YPR disturbances. Balancing includes self-balancing of the main body within the four feet as well as balancing of each foot on the terrain.

The robots YPR sensors detect any disturbance and accordingly update their respective nodes with the intensity of deviation such as roll to left (L), roll to right (R), upward pitch (U), downward

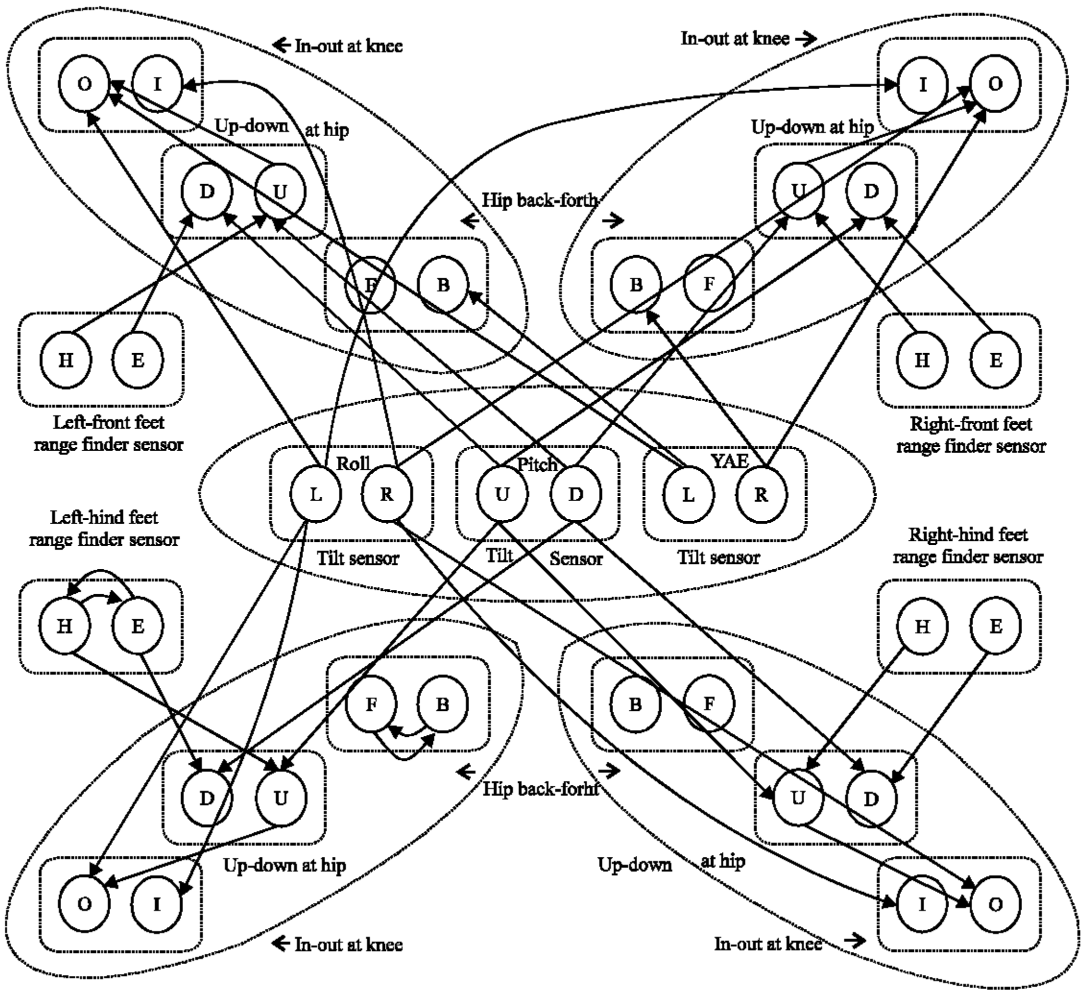

Fig. 2: The developed FCM

pitch (D), yaw left (L) and yaw right (R). These factors are input while the joint variables, i.e., influenced by input factors, are the decision nodes or outputs. The outputs therefore include: backward force for propulsion at hip (B) against forward force at hip (F), downward force at hip for support (D) or upward force at hip for swing (U) and inward or outward forces at knee (I or O) for mediolateral forces to left and right (Biewener, 2003; Vepa, 2009).

There is a two-way causal link connecting each pair of nodes belonging to a joint or a sensor, i.e., any pair of nodes within a perforated box which is not shown here for the sake of brevity. However, this is exemplified for pair nodes (H and E) related to the left-front feet range finder sensor and also for pair nodes (B and F) at left-hind hip. These pairs of links all carry negative weights since the extent (intensity) of each node shall decrease the extent of the other node within the pair.

RESULTS AND DISCUSSION

The system performance has been evaluated on a simulated universal quadruped as shown in Fig. 1. 3d simulation of the robot included conceptual design of mechanical parts, kinematical features of robot locomotion on a typical natural terrain and dynamics including

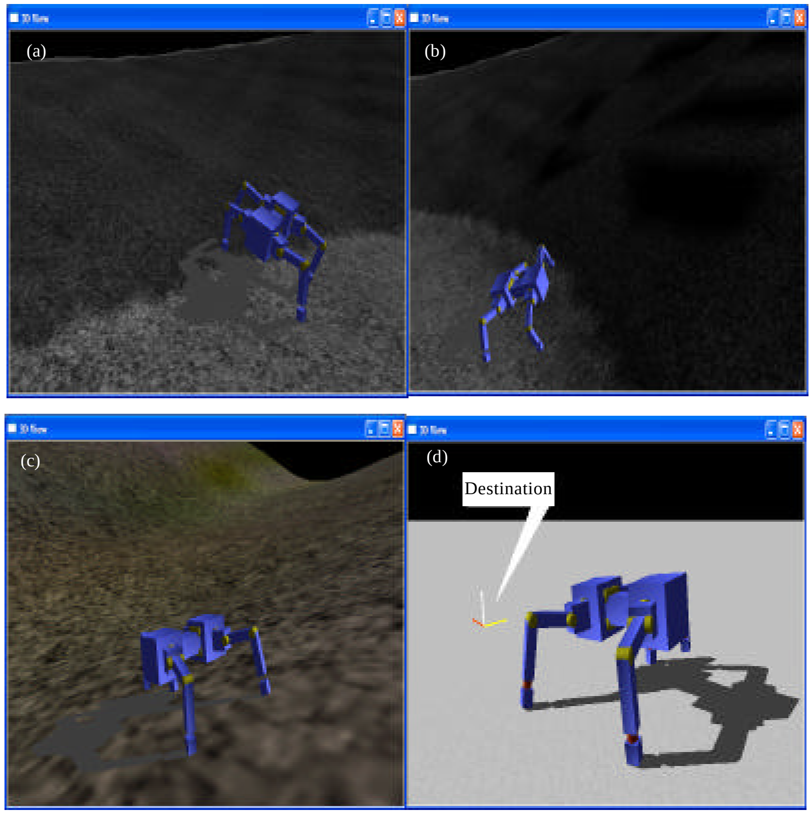

Fig. 3 (a-d): Robot motion (a) on left tilt (b) right tilt and (c) uphill, on uneven terrain (d) Repeatability test on flat terrain

gravity and slippage. As mentioned earlier, gait generation has been resulted from a more complex FCM which was run in the simulation. However, the balancing task has been accomplished merely using the FCM of Fig. 2 which was incorporated as a subroutine within the main FCM. The difference between this subroutine (balancing control) and the main FCM (gait generation) is that the former is a real time process with instant response to any yaw, pitch, roll disturbances sensed at the centre of the mass, i.e., centre of shape in this case and the feet levels, while the latter is a sequential process to facilitate placement of limbs, i.e., left front, right hind, right front, left hind, through alternative support and swing phases.

Figure 3a-d shows much of the achievements in robot's self-balancing. The scenes are taken from the simulation software showing the robot traveling on a left tilt (a) right tilt (b) and uphill (c) in a vast landscape. The robot has managed to sustain itself on roll and pitch along the path. While simulation showed sufficient robustness, tests of repeatability were conducted by assigning a certain start and destination point on the landscape as shown in Fig. 3 (d) from which an accuracy of 1.2 m (distance from the destination point) has been achieved after 20 m of trajectory along straight path. However, it must be noted that the amount of error is attributed to both balancing and gait generation which are mainly due to slippage and other dynamic features.

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