FOOTSTEP PLANNING FOR BIPED ROBOT BASED ON FUZZY Q-LEARNING APPROACH

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Abstract: The biped robots have more flexible mechanical systems and they can move in more complex environment than wheeled robots. Their abilities to step over both static and dynamic obstacles allow to the biped robots to cross an uneven terrain where ordinary wheeled robots can fail. In this paper we present a footstep planning for biped robots allowing them to step over dynamic obstacles. Our footstep planning strategy is based on a fuzzy Q-learning concept. In comparison with other previous works, one of the most appealing interest of our approach is its good robustness because the proposed footstep planning is operational for both constant and random velocity of the obstacle.

1 INTRODUCTION

In contrast with the wheeled robots, the biped robots have more flexible mechanical system and thus they can move in more complex environment. Actually, their abilities to step over both static and dynamic obstacles allow to the biped robots to cross an uneven terrain where regular wheeled robots can fail. Although there are a large number of papers dealing with the field of biped and humanoid robots (see for examples (Hackel, 2007) and (Carlos, 2007)), only a few of publication researches concern the path planning for biped robots (Ayza, 2007), (Chestnutt, 2004), (Sabe, 2004). In fact, the design of a path planning for biped robots into indoor and outdoor environment is more difficult than for wheeled robots because it must take into account their abilities to step over obstacles. Consequently, path planning with obstacle avoidance strategy like the wheeled robots is not sufficient.

Generally, the previous proposed approaches in the field of path planning for biped robots are based on a tree search algorithm. In (Kuffner, 2001) , Kuffner et al. have proposed a footstep planning approach using a search tree from a discrete set of feasible footstep locations. This approach has been validated on the robot H6 (Kuffner, 2001) and H7 (Kuffner, 2003). Later, this strategy has been extended for the robot Honda ASIMO (Chestnutt, 2005). Although the footstep planning proposed by Kuffner seems an interesting way to solve the problem of the path planning for biped robots, the main drawbacks are on the one hand the limitation at 15 foot placements (Kuffner, 2001) in order to limit the computational time, and on the other hand, this approach is operational only in the case of the predictable dynamic environments (Chestnutt, 2005). In this paper, we present a new concept of a footstep planning for biped robots in dynamic environments. Our approach is based on a Fuzzy Q-learning (FQL) algorithm. The FQL, proposed by Glorennec et al. (Glorennec, 1997) (Jouffe, 1998), is an extension of the traditional Q-learning concept (Watkins, 1992) (Sutton, 1998) (Glorennec, 2000) allowing to handle the continuous nature of the state-action. In this case, both actions and Q-function may be represented by Takagi-Sugeno Fuzzy Inference System (TS-FIS). After a training phase, our footstep planning strategy is able to adapt the step length of the biped robot only using a Fuzzy Inference System. However, our study is limited to the sagittal plane and does not take into account the feasibility of the joint trajectories of the leg. In fact, the footstep planning gives only the position of the landing point. But the first investigations show a real interest of this approach because:

- The computing time is very short. After the learning phase, the footstep planning is based only on a FIS,
- The footstep planning is operational for both predictable and unpredictable dynamic environment allowing to increase the robustness.

This paper is organized as follows. In Section 2, the Fuzzy Q-learning concept is presented. Section 3 describes the footstep planning based on the Fuzzy Q-learning. In section 4, the main results, obtained from simulations, are given. Conclusions and further developments are finally set out in section 5.

2 FUZZY Q-LEARNING CONCEPT

Reinforcement learning (Sutton, 1998) (Glorennec, 2000) involves problems in which an agent interacts with its environment and estimates consequences of its actions on the base of a scalar signal in terms of reward or punishment. The goal of the reinforcement learning algorithm is to find the action which maximize a reinforcement signal. The reinforcement signal provides an indication of the interest of last chosen actions. Q-Learning, proposed by Watkins (Watkins, 1992), is a very interesting way to use reinforcement learning strategy. However, the Q-Learning algorithm developed by Watkins deals with discrete cases and assumes that the whole state space can be enumerated and stored in a memory. Because the Q-matrix values are stored in a look-up table, the use of this method becomes impossible when the state-action spaces are continuous. For a continuous state space, Glorenec et al. (Glorennec, 1997) (Jouffe, 1998) proposed to use fuzzy logic where both actions and Q-function may be represented by Takagi-Sugeno Fuzzy Inference System (TS-FIS). Unlike the TS-FIS in which there is only one conclusion for each rule, the Fuzzy Q-Learning (FQL) approach admits several actions per rule. Therefore, the learning agent has to find the best issue for each rule.

The FQL algorithm uses a set of N_K fuzzy rules such as:

$$\text{IF} \quad x_1 \text{ is } M_1^1 \quad \text{AND} \quad x_i \text{ is } M_i^j \quad \text{THEN} \quad \begin{cases} & y_k = a_k^1 & \text{with} & q = q_k^1 \\ \text{or} & y_k = a_k^l & \text{with} & q = q_k^l \\ \text{or} & y_k = a_k^{N_l} & \text{with} & q = q_k^{N_l} \end{cases} \tag{1}$$

x_i ($i = 1..N_i$) are the inputs of the FIS which represent the state space, N_i is the size of the input space. Each fuzzy set j for the input i is modeled by a membership function M_i^j and its membership value μ_i^j. a_k^l and q_k^l are respectively the l^{th} possible action for the rule k and its corresponding Q-value ($k = 1..N_k$;$l = 1..N_l$). At each step time t, the agent observes the present state $X(t)$. For each rule k, the learning system has to choose one action among the total N_l actions using an Exploration/Exploitation Policy (EEP). In our approach, ε-greedy algorithm is used to select the local action for each activated rule. The action with the best evaluation value ($max(q_k^l), l = 1..N_l$) has a probability P_ε to be chosen, otherwise, an action is chosen randomly among all possible actions. After, the execution of the next computed action, the agent may update the Q-value using of a reinforcement signal. The algorithm of the FQL may be decomposed into four stages:

- After the fuzzification of the perceived state $X(t)$, the rule values $\alpha_k(t)$ are computing using equation (2):

$$\alpha_k(t) = \mu_1^j \, \mu_2^j ..... \mu_{Ni}^j \tag{2}$$

- The final action $Y(t)$ is computed through two levels of computation: in the first level, local action l in each activated rule is determined by using EEP, and in the second level global action is calculated as a combination of all local actions. Equations (3) and (4) give respectively the computation of the global action $Y(t)$ and the corresponding $Q(t)$ value according to the truth value $\alpha_k(t)$:

$$Y(t) = \sum_{k=1}^{N_k} \alpha_k(t) a_k^l(t) \tag{3}$$

$$Q(t) = \sum_{k=1}^{N_k} \alpha_k(t) q_k^l(t) \tag{4}$$

- Matching up the new action, given by $Y(t)$ and taking into account the environment's reply, $Q(t)$may be updated using equation (5):

$$\Delta Q(t) = \beta[r + \gamma V_{max}(t+1) - Q(t)] \tag{5}$$

Where $V_{max}(t+1)$ is the maximum Q-value for the activated rule at the next step time $t+1$:

$$V_{max}(t+1) = \sum_{k=1}^{N_k} \alpha_k(t+1) max(Q_k^l(t+1)) \tag{6}$$

γ is a discount factor which can be chosen from 0 to 1. If it is close to 0, the reinforcement information tends to consider only the immediate reward, while if it is closer to 1, it considers the future

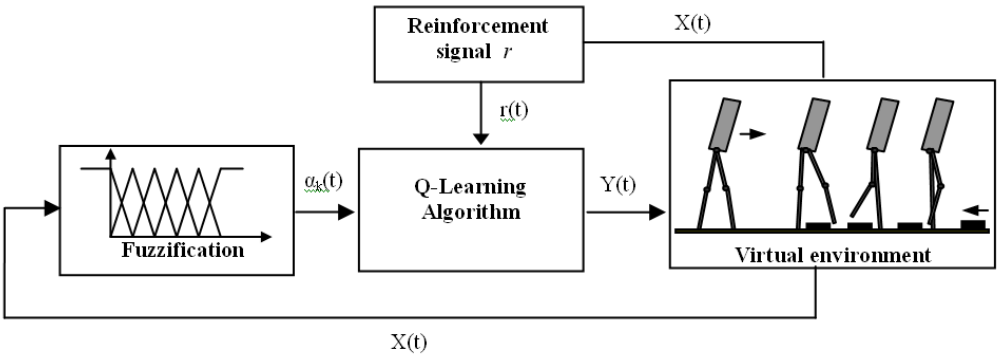


Figure 1: Footstep planning strategy.

rewards with greater weight. β is a learning rate parameter allowing to weight the part of the old and new rewards in a reinforcement signal r.

- Finally, for each activated rules, the corresponding elementary quality Δq_k^l of the Q-matrix is updated as:

$$\Delta q_k^l = Q(t)\alpha_k(t) \tag{7}$$

3 FOOTSTEP PLANNING

The proposed footstep planning is based on a FQL approach. Our aim is to design a control strategy allowing to adjust automatically the step length of a biped in order that the robot avoids dynamic obstacles by using step over strategy. As figure 1 shows it, our footstep planning may be divided into four parts:

- The first part involves a fuzzification of inputs of the state X(t),
- The second concerns the FQL algorithm allowing to compute the length of the step,
- The third part allows simulating dynamic environment into which the robot moves,
- And the fourth part gives the reinforcement signal.

3.1 Virtual Dynamic Environment

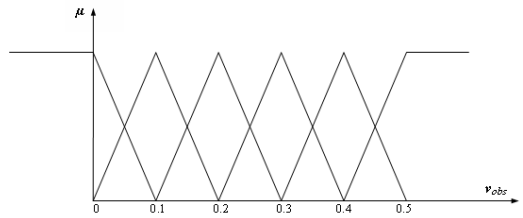
The both robot and obstacle move in sagittal plane but in opposite directions. We consider that the walking of the biped robot may include as well strings of single support phases (only one leg is in contact with the ground) as instantaneous double support phases (the two legs are in contact with the ground). The biped robot may adjust the length of its step but we consider that the duration of each step is always equal to 1s. The size and velocity of the obstacle are included into $[0, 0.4m]$ and $[0, 0.4m/s]$ ranges respectively. Although the robot has the ability to adjust its step length, there are two possibilities in which the robot may crash with the obstacle. First one occurs when the length of the step is not correctly adapted according to the position of the dynamic obstacle. In this case, the swing leg touches directly the obstacle during a double support phase. The other case corresponds to the situation where the obstacle collides with the stance leg during the single or double support phase.

3.2 Fuzzification

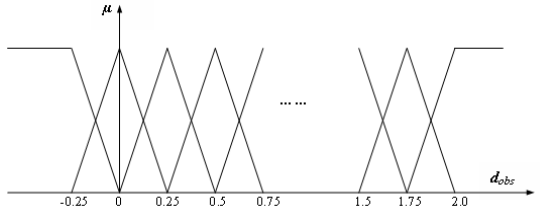
The design of our footstep planning is based on both Takagi-Sugeno FIS and Q-learning strategies. Consequently, it is necessary to use a fuzzification for each input. In the proposed approach, we use two inputs in order to perform a correct footstep planning. These inputs are the distance between the robot and the obstacle d_{obs} and the velocity of the obstacle v_{obs}. d_{obs} and v_{obs} are updated at each double support phase. d_{obs} corresponds to the distance between the front foot and the first side of the obstacle. v_{obs} is computed from the distance covered during 1s. The fuzzification of v_{obs} and d_{obs} is carried out by using respectively 6 and 11 triangular membership functions. Figure 2(a) and 2(b) gives the membership functions of the obstacle velocity and distance respectively.

3.3 FQL-based Step Length

The FQL algorithm uses a set of fuzzy rules such as equation (1). For the proposed problem, the number of the rules is 66 (6 and 11 membership functions for velocity and distance of the obstacle respectively). For each rules, we define 5 possible outputs which are $[0.1, 0.2, 0.3, 0.4, 0.5]m$. In fact, these outputs cor-



(a) Obstacle velocity v_{obs} (in m/s).



(b) Obstacle distance d_{obs} (in m).

Figure 2: Membership functions used for the input space.

respond to the length of the step. Consequently, at each step time, the Fuzzy Q-Learning algorithm needs to choose one output among five possible outputs for each activated rules. It must be pointed out that the chosen output is included into a discrete set, but the real output $Y(t)$ is a real number dues a fuzzification. During the simulation, the size of the obstacle is constant but the velocity of the obstacle may be modified. At each episode, initialization of some parameters are necessary. The initial distance between the biped robot and the obstacle is always equal to $2.5m$. The velocity of the obstacle is chosen randomly into the interval $[0,0.4]m/s$. During one episode, the step length of the robot is computed using the FQL algorithm described in section 2. Consequently, the biped robot moves step by step towards the obstacle during the episode. The episode is finished whether the robot steps over the obstacle (success) or if the robot crashes into obstacle (failure). The discount factor γ and the learning rate parameter β are equal to 0.8 and 0.1 respectively. This parameters have been chosen empirically after several trials in order to assure a good convergence of FQL algorithm. The probability P_ε is equal to 0.1 and means that the random exploration is privileged during the learning phase.

3.4 Reinforcement Signal

The reinforcement signal provides an information in terms of reward or punishment. Consequently, the reinforcement signal informs the learning agent about the quality of the chosen action. In our case, the learning agent must find a succession of action allowing to the biped robot to step over an obstacle. But here the obstacle is a dynamic object which moves towards the biped robot. Consequently, the reinforcement information have to take into account of the velocity of the moving obstacle. In addition, the position of the foot just before the stepping-over is very important as well. On the base of these considerations, we designed reinforcement signal in two parts.

Firstly, if $x_{rob} < x_{obs}$ where x_{rob} and x_{obs} give the positions of the robot and of the obstacle respectively:

- $r = 0$, if the robot is still far from obstacle,
- $r = 1$, if the position of the robot is appropriate to cross the obstacle at next step,
- $r = -1$, if the robot is too close to the obstacle.

In this first case, r is computed with the following equation:

$$r = \begin{cases} 0 & \text{if} \quad (\, x_{rob} \leq (x_{obs} - 1.2 v_{obs} \Delta t)\,) \\ 1 & \text{if} \quad (x_{rob} > (x_{obs} - 1.2 v_{obs} \Delta t)) \\ & \quad AND \;\; (x_{rob} \leq (x_{obs} - 1.1 v_{obs} \Delta t)). \\ -1 & \text{if} \quad (x_{rob} > (x_{obs} - 1.1 v_{obs} \Delta t)) \end{cases} \tag{8}$$

x_{rob} and x_{obs} are updated after each action. $v_{obs}\Delta t$ represents the distance covering by obstacle during the time Δt. As the duration of the step is always equal $1s$, Δt is always equal to $1s$.

Secondly, if ($x_{rob} \geq x_{obs}$):

- $r = -2$, if the robot crashes into the obstacle at the next step,
- $r = 2$, if the robot crosses the obstacle at the next step.

In this last case, r is given by equation (9).

$$r = \begin{cases} -2 & \text{if} \quad (\, x_{rob} \leq (x_{obs} + L_{obs})\,) \\ 2 & \text{if} \quad (\, x_{rob} > (x_{obs} + L_{obs})\,) \end{cases} \tag{9}$$

Where L_{obs} is the size of the obstacle.

4 SIMULATION RESULTS

In this section, we present the main results related the footstep planning based on FQL approach by using MATLAB software. It must be noticed that our goal is to design a control strategy allowing to give a path planning into a dynamic environment for biped robot but we do not take into account the dynamic of the biped robot. We consider only discrete information allowing to compute the landing position of the foot. In addition, we consider only flat obstacles in the following simulations.

4.1 Training Phase

During the training phase, the goal of the learning agent is to find the best rules in order that the biped robot crosses the obstacle. On the base of the previous description, we trained the Q-matrix during 10000 episodes. After a full training, we test the footstep planning approach with 1000 velocity samples covering uniformly the input range $[0,0.4]m/s$.

Table 1 gives results about successes rate for four sizes of the obstacle. The rate success corresponds to the ratio between the number of successes and the totality of trials (1000). And the figure 3 shows an example of the repartition between the successes and the failures over an input range v_{obs} and when L_{obs} is equal to $0.2m$. When the robot can step over the obstacle successfully, the results is 1 otherwise it is 0.

Table 1: Rate success according to obstacle size.

Size (m)	0.1	0.2	0.3	0.4
Successes rate (%)	65.6	31.3	21.7	4.8

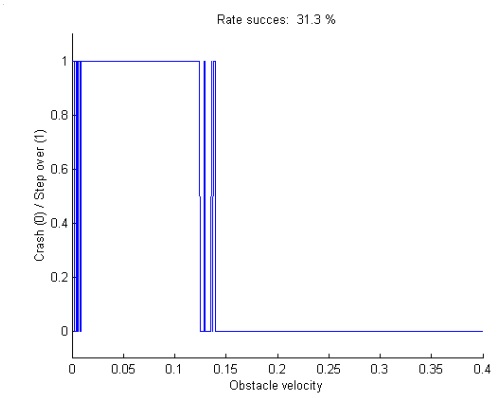


Figure 3: Successes rate when the size of the obstacle is equal to $0.2m$.

It must be pointed out that more the size is large, more the successes rate is weak. And like figure 3 shows it, there is a threshold ($0.12m/s$ approximatively when $L_{obs} = 0.2m$) where our footstep planning never finds a solution. Consequently, the velocity of the obstacle must be limited if we want the biped crosses the obstacle successfully.

4.2 Footstep Planning Examples

Figure 4 shows a footstep sequence when the robot crosses an obstacle. The size of the obstacle is equal to $0.2m$ and its velocity is constant during all the simulation. Rectangles indicate the obstacle and the spots indicate the two positions of the feet (left and right) for each step. Table 2 gives the step length for all the steps. It must be pointed out that when the biped robot is close to the obstacle, then the length of the step decreases in order to prepare the stepping over. Finally, the last step allows to avoid obstacle without collision.

Table 2: Length of the step L_{step} when $v_{obs} = 0.1m/s$ and $L_{obs} = 0.2m$.

Step	1	2	3	4	5	6
L_{step}	0.50	0.22	0.50	0.45	0.13	0.50

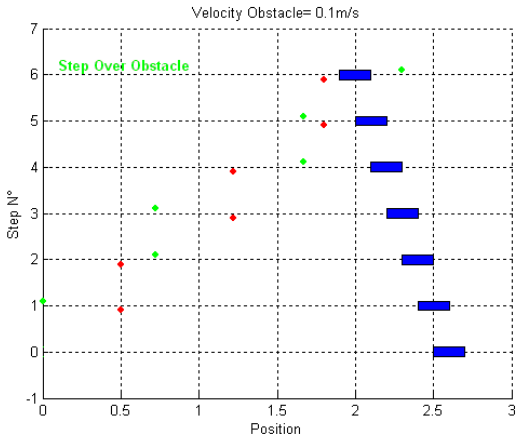


Figure 4: Successful footstep planning when $v_{obs} = 0.1m/s$ and $L_{obs} = 0.2m$.

It is pertinent to note that one of the most interesting point in our approach is its abilities to operate when the velocity of the obstacle is not constant. Figure 5 shows the footstep sequence when the obstacle moves with a random velocity. The velocity of the obstacle is carried out by the sum of a constant value which is equal to $0.1m/s$ and a random value included into $[-0.1..0.1]m/s$. Table 3 gives V_{obs} and L_{step} for each step. The size of the obstacle is equal to $0.1m$. It must be pointed out that the control strategy allows to adapt automatically the length of the step according to the obstacle velocity thanks to FQL algorithm. For 1000 trials realized in the same conditions, the successes rate is equal to 85% approximatively. This is very interesting because our strategy allows to increase the robustness of the footstep planning.

5 CONCLUSIONS

In this paper we have presented a footstep planning strategy for biped robots allowing them to step over

Table 3: Length of the step when v_{obs} is random and $L_{obs} = 0.1m$.

Step	1	2	3	4	5	6
v_{obs}	0.14	0.05	0.16	0.10	0.16	0.04
L_{step}	0.50	0.23	0.37	0.44	0.10	0.50

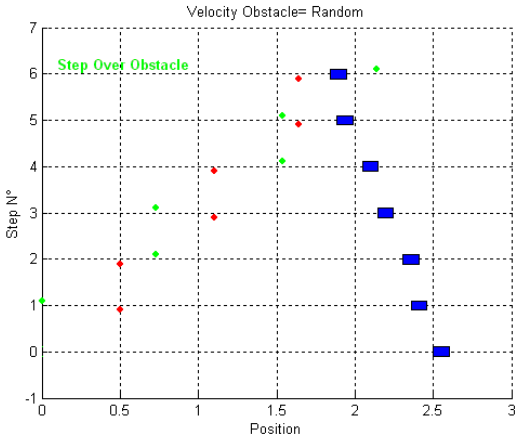


Figure 5: successful footstep planning when v_{obs} is random, $L_{obs} = 0.1m$.

dynamic obstacles. Our footstep planning tactic is based on a fuzzy Q-learning concept. The most appealing interest of our approach is its outstanding robustness related to the fact that the proposed footstep planning is operational for both constant and variable velocity of the obstacle.

Futures works will be focus on the improvement of our footstep planning strategy:

- First, our actual control strategy does not take into account the duration of the step. However, this parameter is very important with dynamic obstacles. Therefore, our goal is to enhance the proposal footstep planning in order to take care about both the length and the duration of the step,
- Second, in some cases, biped robot can not step over obstacle: for example when the size of the obstacle is too large. Consequently, the footstep planning must be able to propose a path planning in order to make the robot avoid obstacle.
- Third, in long-term, our goal is to design more general footstep planning based on both local footstep planning and global path planning,
- Finally, experimental validation may be consider on real humanoid robot. But in this case, it is necessary to design the joint trajectories based on the position of feet.

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