Revision on fuzzy artificial potential field for humanoid robot path planning in unknown environment

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Abstract: Path planning in a completely known environment has been experienced various ways. However, in real world, most humanoid robots work in unknown environments. Robots' path planning by artificial potential field and fuzzy artificial potential field methods are very popular in the field of robotics navigation. However, by default humanoid robots lack range sensors; thus, traditional artificial potential field approaches needs to adopt themselves to these limitations. This paper investigates two different approaches for path planning of a humanoid robot in an unknown environment using fuzzy artificial potential (FAP) method. In the first approach, the direction of the moving robot is derived from fuzzified artificial potential field whereas in the second one, the direction of the robot is extracted from some linguistic rules that are inspired from artificial potential field. These two introduced trajectory design approaches are validated though some software and hardware in the loop simulations and the experimental results demonstrate the superiority of the proposed approaches in humanoid robot real-time trajectory planning problems.

Keywords: humanoid robots; path planning; unknown environment; artificial potential field.

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1 Introduction

Ideally, we expect that robots work similar to expert labours and we want robots to work in industry with or instead of human labour forces. Robots that have same physical body as human bodies are more useful than other types, because human beings have built their environments in proportion to their ergonomic (Tsay and Lai, 2009). Still, it is not possible to build humanoid robots totally adapted with industrial environments. Stability, mapping, interacting, computing and grasping are some research gaps, and path planning make humanoid robots' navigation an open problem (Du et al., 2012). The ultimate goal for humanoid robot is a robot to work in every environment. Since the real world is dynamic, saving all environments in robot memory is impossible. This means humanoid robots must work in unknown environments.

Path planning problem has been investigated in several research works (Dai and Yang, 2012). Trajectory planning for a mobile robot to move from an initial position to a target position in a known environment is a well-known problem in robotics. There are some methods in path planning for unknown environment, for example fuzzy logic based methods have been used in some research projects (Liu and Yu, 2012).

A fuzzy-based navigator has been proposed by Zavlangas et al. (2000) for obstacle avoidance and navigation problem of omnidirectional mobile robots. The proposed navigator considers only the nearest obstacle to decide upon the robot next move. This method has been established based on three parameters, which are the distance between the robot and the nearest obstacle, the angle between the robot and the nearest obstacle, and the angle between the robots direction and the straight line connecting the current position of the robot and the goal configuration. Although the presented method has been evaluated as an accurate and real-time method, but these three parameters cannot be prepared in one camera humanoid robots. In other word, this method needs omnidirectional range sensors.

A useful method to deal with the problem of wheeled mobile robot navigation has been demonstrated by Fatmi et al. (2006). Issues such as individual behaviour design and action coordination of the behaviours were addressed by fuzzy logic. The coordination technique employed in this work includes two layers. A layer of primitive basic behaviours and the supervision layer which is based on the context make a decision about which behaviour(s) to process (activate) rather than processing all behaviour(s) and then blends the appropriate ones, as a result time and computational resources are saved. This method employs 14 range sensors to achieve position of any obstacle around of the robot and so cannot be used in most humanoid robots.

Iancu et al. (2010) have presented a fuzzy reasoning method of Takagi-Sugeno type controller and has applied this in two wheels autonomous robot navigation. This mobile robot is equipped with a sensorial system. The robot sensors area is divided into seven radial sectors labelled as: large left, medium left and small left for the left areas, EZ for the straight area, and large right, medium right and small right for the right area, respectively. Each radial sector has been further divided in other three regions like small, medium and large. The range of applied sensors were able to recognise up to 30 metres, and the robot could identify an obstacle anywhere inside the interval between –90 and 90 degree. Indisputably, most humanoid robots have not the same sensors and therefore, this way is not feasible for humanoid robots.

The simplest path planning algorithms for unknown environment are called bug algorithms. Bug algorithms solve the navigation problem by storing only a minimal number of way points, but without generating a full map of the environment. Traditional bug algorithms (Lumelsky and Stepanov, 1984; Sankaranarayanar and Vidyasagar, 1990; Noborio, 1990, 1992; Horiuchi and Noborio, 2001) worked only with tactile sensors. Continuously updating position data is mandatory when bug algorithms are used. As we know, it is not possible to achieve a continuous data updating in practice. In addition, the bug models make some simplifying assumptions such as the robot is a point object has perfect localisation ability and perfect sensors. These three assumptions are unrealistic for real robots, and therefore, bug algorithms are usually not directly applied in practical navigation tasks. New bug algorithms such as dist-bug (Kamon and Rivlin, 1997), vis-bug (Lumelsky and Skewis, 1990), tangent-bug (Kamon et al., 1998) and sens-bug (Kim et al., 2003), unlike old ones work with range sensors.

Besides, a path planning algorithm for humanoid robots is proposed by Michel et al. (2005). There algorithm needs information of position of robots and obstacles as input data. So they used an external camera to show a top view from environment. Unfortunately, in most situations, the camera failed to prepare a global view from robot working environments. Other path planning project on HRP-2 humanoid robot has been done by Michel et al. (2006). Their method used several cameras in robot environment to produce a map. As we know using cameras wherever we want to use humanoid robots is not practical.

In addition, Nakhaei and Lamiraux (2008) used online 3D mapping and combined it with path planning. They used 3D occupancy grid that was updated incrementally by stereo vision for constructing the model of the environment. A roadmap based method was used for path planning, because the dimension of the configuration space is high for humanoid robots. Indeed, it is necessary to update the roadmap after receiving new visual information because the environment is not static. The test results on HRP2 were not acceptable, due to long time processing; this algorithm needs exact stereo vision and a lot of time to find a path in each step.

Furthermore, Sabe et al. (2004) have presented a method for path planning and obstacle avoidance for the QRIO humanoid robot. The mentioned robot allowed walking autonomously around a home environment. A* algorithm was used in this method that needed a lot of time to process. Moreover, they used online mapping and stereo vision. Their method seems effective, but it needed high computational processes in addition to stereo vision. As a result, this method is not applicable in most conditions too.

Additionally, in another study, best-first search and A* algorithms has been used for foot step path planning on H7 humanoid robot by Chestnutt et al. (2003). This research showed that A* is more effective than best-first search. But it is important to know that both of them need stereo vision and high computational processes.

Okada et al. (2003) have presented another way for humanoid robot path planning. In this way, robot and obstacle were supposed as cylindrical shapes. In this research, based on vision, the robot extracted the floor map and made decision. This method encountered to a big bug when robot started in front of a big obstacle, because it could not find the floor and so path finding was disturbed.

Also, artificial potential field algorithm has been employed in a recent path planning research on an iCub (a humanoid robot) by Gay et al. (2010). In this algorithm, iCub calculated 3D position of each obstacle Firstly, and then transform it into 2D, and calculated artificial potential field. Their method needed exact image understanding to find position of obstacles. Therefore, it was not applicable in some humanoid robots.

This paper suggests two new distinct methodologies for producing artificial potential field by fuzzy inference systems and by using only one camera in a humanoid robot. In the first method, artificial potential field is calculated by fuzzified relations; and in the second method, some linguistic rules give direction of artificial potential field. It is supposed that humanoid robots have a camera and an odometer. These two introduced trajectory design approaches are compared with each other though some software and hardware in the loop simulations and the experimental results demonstrate the superiority of the proposed approaches in humanoid robot real-time trajectory planning problems.

2 Problem statement and functional block diagram

In path planning process, the location of the obstacles or the forbidden zones and free spaces must be clarified for the mobile robots. In the humanoid robots, this information could be achieved from a vision system. To meet this purpose, firstly the images are segmented. For added safety margins, dilation process can be used. Dilation means expanding the obstacles to obtain a configuration space (Choset et al., 2005). Figure 1 shows the functional block diagram of both proposed methods.

Figure 2 shows original images in comparison with the segmented and the final images. Humanoid robots' cameras are usually located in the head of humanoid robots and have an elevation angle with the local horizon. Therefore, captured images may be defined in perspective styles.

Figure 3 shows the effect of the perspective view on a checkerboard. Therefore, in order to extract the distances from images, the image is meshed non-homogeneously. Because the angle and height of the camera is considered fixed approximately, the obstacle location with respect to robot could be found by pre-measuring of the centre of each box.

In the first method, the robot computes the artificial potential field of each box of the image. Then, total artificial potential field is extracted with fuzzy inference. At the end, robot moves according the artificial field.

In the second method, the membership function of any working spaces, including the target, free spaces and the obstacles, for each part could be calculated. Then, fuzzy inference system simulates the artificial potential field using the linguistic rules to provide a reliable passage for robot movement.

Figure 1 Functional block diagram for humanoid robot path planning with fuzzy artificial potential (FAP) fields

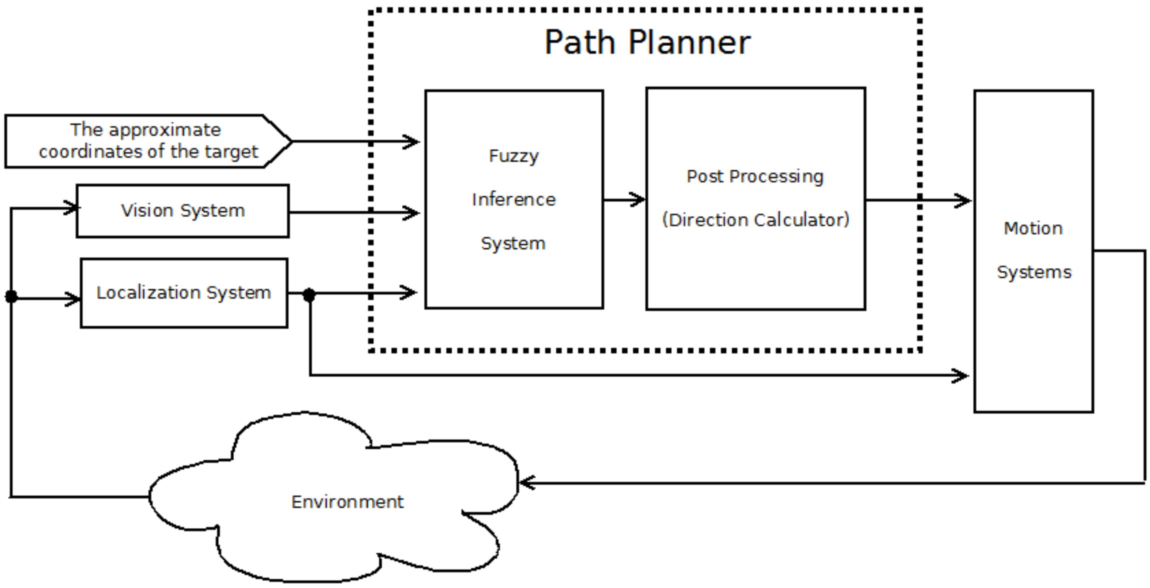
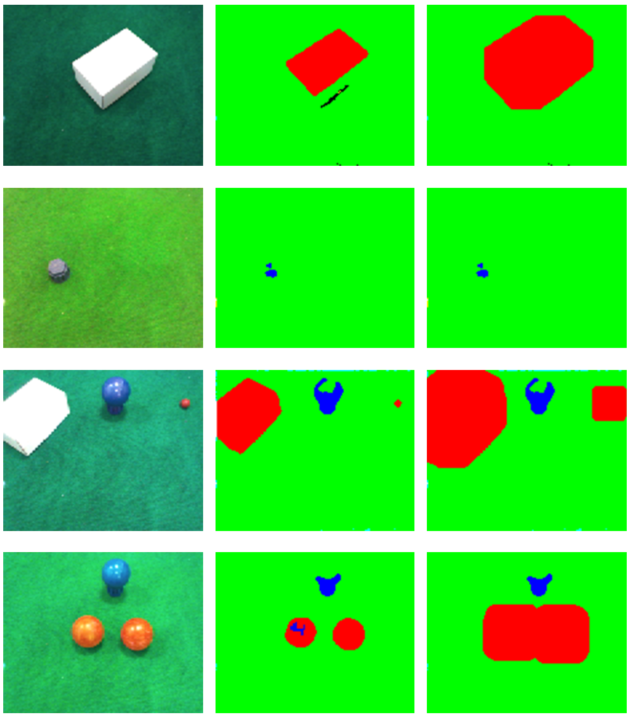


Table 1 Comparison our method with others

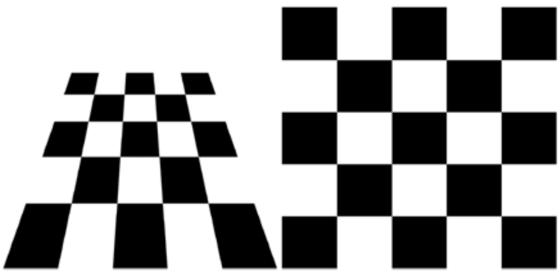
Method	*Real-time*	*Work with approximate positions*	*Vision*	*Map*	*Work on front of obstacle*
Nakhaei and Lamiraux (2008)	×	×	Stereo	3D	✓
Sabe et al. (2004)	×	×	Stereo	2D	✓
Chestnutt et al. (2003)	×	×	Stereo	2D	✓
Okada et al. (2003)	×	×	Stereo	Floor (3D)	×
Gay et al. (2010)	×	×	Stereo	Independent	✓
Our methods	✓	✓	Mono	Independent	✓

Figure 2 (a) Original images, (b) segmented images (c) final images (see online version for colours)



(a) (b) (c)

Figure 3 Example of effect of camera's angle (a) top view (b) perspective view



(a) (b)

Some prevalent researches on path planning strategies in unknown environment are listed in Table 1, and as we can see some of these methods need range sensors that are not applicable on humanoid robot and the others are not real-time.

Superposition principle could be employed with potential field approach to accelerate the path planning procedure. Furthermore, resorting to fuzzy analysis has obviated the necessity of having knowledge of the precise shape, position and orientation of the surrounding obstacles, as well as the need for relatively enormous volumes of memory for stocking information gathered in 2D and 3D maps.

3 Problem definition and formulation

3.1 Fuzzification with Takagi-Sugeno method

The resultant force in a traditional potential field could be defined as follows:

$$\vec{F} = \vec{F}_a - \sum_k \vec{F}_d(k) \tag{1}$$

where $\vec{F}_a$ is the attractive force and $\vec{F}_d(k)$ is the distractive force of k^{th} obstacle. In a 2D discrete space, equation (1) could be re-written as follows:

$$\vec{F} = \vec{F}_a - \sum \vec{F}_d(i, j) \tag{2}$$

Equation (2) could be decomposed in x and y directions as follows:

$$\begin{cases} F_x = F_{ax} - \sum F_{dx}(i, j) \\ F_y = F_{ay} - \sum F_{dy}(i, j) \end{cases} \tag{3}$$

In which:

$$\begin{cases} F_{ax} = \vec{F}_a \cdot \dfrac{\vec{x}_t}{|\vec{r}_t|} \\ F_{ay} = \vec{F}_a \cdot \dfrac{\vec{y}_t}{|\vec{r}_t|} \\ F_{dx}(k) = \vec{F}_d(k) \cdot \dfrac{\vec{x}(i, j)}{|\vec{r}(i, j)|} \\ F_{dy}(k) = \vec{F}_d(k) \cdot \dfrac{\vec{y}(i, j)}{|\vec{r}(i, j)|} \end{cases} \tag{4}$$

By substituting equation (4) in to equation (3), we will have:

$$\begin{cases} F_x = \vec{F}_a \dfrac{\vec{x}_t}{|\vec{r}_t|} - \sum \vec{F}_d(i, j) \cdot \dfrac{\vec{x}(i, j)}{|\vec{r}(i, j)|} \\ F_y = \vec{F}_a \cdot \dfrac{\vec{y}_t}{|\vec{r}_t|} - \sum \vec{F}_d(i, j) \cdot \dfrac{\vec{y}(i, j)}{|\vec{r}(i, j)|} \end{cases} \tag{5}$$

By inspiration of the gravity potential field principal in defining the attractive and distractive forces, equation (5) will be expanded as follows:

$$\begin{cases} F_x = k_a \dfrac{\vec{x}_t}{|\vec{r}_t|^3} - k_d \sum \dfrac{\vec{x}(i, j)}{|\vec{r}(i, j)|^3} \\ F_y = k_a \dfrac{\vec{y}_t}{|\vec{r}_t|^3} - k_d \sum \dfrac{\vec{y}(i, j)}{|\vec{r}(i, j)|^3} \end{cases} \tag{6}$$

Equation (5) is a crisp artificial potential field equation. It shows that for calculating the artificial potential field, a robot needs exact distance of each pixel to the robot. As it was mentioned, due to the use of only one camera without range sensors in many humanoid robots, calculating the exact distance is impossible. To solve this problem, we suggest that instead of using pixel data, robot uses a set of pixels, i.e., the square between meshes of image. In this way robot must calculate the membership function of each meshes for obstacle, target, and free spaces, as follows:

$$P(i, j) = \frac{number\ of\ obstacle\ pixels\ in\ square\ (i, j)}{number\ of\ all\ pixels\ in\ square\ (i, j)} \tag{7}$$

Membership function of each square to obstacle could be defined as follows:

$$\mu(i, j) = f\left(P(i, j)\right) \tag{8}$$

In the above equation, f is an ascending function which $f(0) = 0$ and $f(1) = 1$. In other words, if there is no obstacle in square, the output must be zero; and if all pixels in the square show obstacle, the output must be one. The simplest function that could be effective in this work is identity function. The fuzzified of equation (6) is:

$$\begin{cases} F_x = k_a \dfrac{\vec{x}_t}{|\vec{r}_t|^3} - k_d \sum \mu(i, j) \dfrac{\vec{x}_t}{|\vec{r}(i, j)|^3} \\ F_y = k_a \dfrac{\vec{y}_t}{|\vec{r}_t|^3} - k_d \sum \mu(i, j) \dfrac{\vec{y}(i, j)}{|\vec{r}(i, j)|^3} \end{cases} \tag{9}$$

Therefore, the direction of the mobile robot path is determined as follows:

$$\theta = \arctan 2\left(k_a \frac{\vec{y}_t}{|\vec{r}_t|^3} - k_d \sum \mu(i\ j) \frac{\vec{y}(i, j)}{|\vec{r}(i, j)|^3},\ k_a \frac{\vec{x}_t}{|\vec{r}_t|^3} - k_d \sum \mu(i, j) \frac{\vec{x}(i, j)}{|\vec{r}(i, j)|^3} \right) \tag{10}$$

where

$$a\tan 2(y, x) = \begin{cases} \arctan \dfrac{y}{x} & x > 0 \\ \arctan \dfrac{y}{x} + \pi & x < 0, y \ge 0 \\ \arctan \dfrac{y}{x} - \pi & x < 0, y < 0 \\ +\dfrac{\pi}{2} & x = 0, y > 0 \\ -\dfrac{\pi}{2} & x = 0, y < 0 \\ undefined & x = 0, y = 0 \end{cases} \tag{11}$$

Since the potential field force is related to the inverse of distance, as the distance tends to zero, then the force tends to infinity. Therefore the distractive force has been discretised in order to avoid from singularity conditions and for eliminating singularity condition in the attractive forces (goal potential) denominator has been changed in to a small non-zero number.

$$\theta_{new} = \arctan 2\left(k_a \frac{\vec{y}_t}{|\vec{r}_t|^3 + 1} - k_d \sum \mu(i, j) \frac{\vec{y}(i, j)}{|\vec{r}(i, j)|^3},\ k_a \frac{\vec{x}_t}{|\vec{r}_t|^3 + 1} - k_d \sum \mu(i, j) \frac{\vec{x}(i, j)}{|\vec{r}(i, j)|^3} \right) \tag{12}$$

Also, the filed lines in real potential field are connected to each other. This property could be found in continuous artificial potential field. When the mobile robot working space is discretised, the calculated artificial potential field could be representative of the artificial potential field of the box centre. Because continuous artificial potential field of each point is different from the discrete artificial potential field, the field lines of discrete artificial potential field does not have the same property of the continuous one. In other words, field lines in discrete artificial potential field collide with each other. Discretising could make oscillation or rotation in robots motion. In order to avoid from this situation, saturation function could alleviate this problem. Instead of computing the direction of the potential field, it is sufficient to calculate the saturation function as follows:

$$\theta_{final} = Sat\left(\theta_{new}, \alpha\right) \tag{13}$$

where

$$Sat(\varnothing, \alpha) = \begin{cases} -\alpha, & \varnothing < -\alpha \\ \varnothing, & -\alpha \le \varnothing < \alpha \\ \alpha, & \varnothing > \alpha \end{cases} \tag{14}$$

As a result, we will have:

$$\theta_{final} = Sat\left(\arctan 2\left(k_a \frac{\vec{y}_t}{|\vec{r}_t|^3+1} - k_d \sum \mu(i, j)\frac{\vec{y}(i, j)}{|\vec{r}(i, j)|^3}, k_a \frac{\vec{x}_t}{|\vec{r}_t|^3+1} - k_d \sum \mu(i, j)\frac{\vec{x}(i, j)}{|\vec{r}(i, j)|^3}\right), \alpha\right) \quad (15)$$

3.2 Fuzzification with Mamdani method

In the logic inspired from Mamdani fuzzification method, questions about the trajectory direction do not involve any mathematical responses. In the other word, the response is including some linguistic phrases such as 'near', 'far', and so on. In the same way, it is possible to define some linguistic phrases to guide a robot. The Mamdani method may help us to implement these linguistic phrases for a mobile robot.

The effect of each pixel could be calculated using the traditional potential field, i.e., equation (7). In order to apply this methodology, at first, the robot onboard computer must calculate the membership function of each mesh for obstacle, target, and free spaces as follows:

$$\begin{cases} P_o(i, j) = \dfrac{number\ of\ obstacle\ pixels\ in\ square\ (i, j)}{number\ of\ all\ pixels\ insquare\ (i, j)} \\ P_f(i, j) = \dfrac{number\ of\ free\ pixels\ in\ square\ (i, j)}{number\ of\ all\ pixels\ in\ square\ (i, j)}, \\ P_t(i, j) = \dfrac{number\ of\ target\ pixels\ in\ square\ (i, j)}{number\ of\ all\ pixels\ in\ square\ (i, j)} \end{cases} \quad (16)$$

$$\begin{cases} \mu_o(i, j) = f\left(P_o(i, j)\right) \\ \mu_f(i, j) = f\left(P_f(i, j)\right) \\ \mu_t(i, j) = f\left(P_t(i, j)\right) \end{cases}$$

In the equation (16), f is an ascending function which $f(0) = 0$ and $f(1) = 1$. In other words, if there is no obstacle in the square, the output must be zero; and if all pixels in the square involve obstacle, the output must be one and so on. According to artificial potential field, the force that is created by a near object is greater than one which is created by the farther object. Based on the above description, we wrote rules in Tables 2 to 5. In these tables, 'V' means very; 'Z' means zero; 'S' means small; 'M' means medium; 'B' means big; 'P' means positive; 'N' means negative; 'A' means attraction case; 'R' means repulsion case.

Table 2 Linguistic rules for axis X repulsion

*j**i*	*–2*	*–1*	*0*	*1*	*2*
5	VSPR	VSPR	Z	VSNR	VSNR
4	VSPR	VSPR	Z	VSNR	VSNR
3	SPR	SPR	Z	SNR	SPR
2	MPR	MPR	Z	MNR	MNR
1	BPR	VBPR	Z	VBNR	BNR

Table 3 Linguistic rules for axis Y repulsion

*j**i*	*–2*	*–1*	*0*	*1*	*2*
5	VSNR	VSNR	VSNR	VSPR	VSPR
4	VSNR	SNR	SNR	SNR	VSNR
3	SNR	MNR	MNR	MNR	SNR
2	MNR	BNR	VBNR	BNR	MNR
1	MNR	VBNR	VBNR	VBNR	MNR

Table 4 Linguistic rules for axis X attraction

*j**i*	*–2*	*–1*	*0*	*1*	*2*
5	VSNA	VSNA	Z	VSPA	VSPA
4	VSNA	VSNA	Z	VSPA	VSPA
3	SNA	SNA	Z	SPA	SPA
2	MNA	MNA	Z	MPA	MPA
1	BNA	VBNA	Z	VBPA	BPA

Table 5 Linguistic rules for axis Y attraction

*j**i*	*–2*	*–1*	*0*	*1*	*2*
5	VSPA	VSPA	VSPA	VSPR	VSPR
4	VSPA	SPA	SPA	SPA	VSPA
3	SPA	MPA	MPA	MPA	SPA
2	MPA	BPA	VBPA	BPA	MPA
1	MPA	VBPA	VBPA	VBPA	MPA

Usually, the attraction force may be greater than the repulsion force. In the other word, MPA > MPR and VSNA < VSNR.

To extract the resultant number from these tables, there are a lot of ways to defuzzify the results of the mentioned rules. Because the natural potential field has super position property, the weighted average method of defuzzification may be chosen as follows:

$$\begin{cases} F_x = \dfrac{\sum_{k=1}^{N}\left(\mu_o^k.\hat{f}_{rx}^k + \mu_t^k.\hat{f}_{ax}^k\right)}{\sum_{k=1}^{N}\left(\mu_o^k + \mu_t^k\right)} \\ F_y = \dfrac{\sum_{k=1}^{N}\left(\mu_o^k.\hat{f}_{ry}^k + \mu_t^k.\hat{f}_{ay}^k\right)}{\sum_{k=1}^{N}\left(\mu_o^k + \mu_t^k\right)} \end{cases} \quad (17)$$

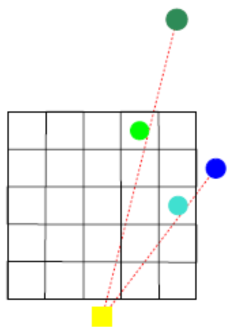
In equation (17), F_x is force in x direction; F_y is force in y direction; N is number of meshes; μ_t^k is membership function of the target in k^{th} square; μ_o^k is membership function of obstacle in k^{th} square; f_{rx}^k will produce a repulsive force in x direction if the k^{th} mesh involves an obstacle; $\hat{f}_{ax}^k$ will produce an attractive force in x direction if the k^{th} mesh involves the target; $\hat{f}_{ry}^k$ will produce a repulsive force in y direction if the k^{th} mesh involves an obstacle; $\hat{f}_{ay}^k$ will produce an attractive force in y direction if the k^{th} mesh involves the target.

Although other methods could be applicable, but weighted average method is more coincident to nature of potential field.

According to the nature of the potential field, the robot should have non-zero magnitude for attractive force. When robot may not able to find the target, sub-goal is necessary for robot movement toward the real target.

Sub-goal is defined as a virtual goal in vision space that achieving it could help us to conduct the robot in to the original target. Figure 4 shows how sub-goal state could be calculated. As it could be seen, if the target is considered as a dark green circle, then the assumed state with light green will be sub-goal; in a similar way, if blue circle is chosen as the target, then the state with cyan circle will be sub-goal state. After determination of sub-goal, the robot could assume that it is the real goal and then may apply the equation (17).

Figure 4 Example of determining sub-goal states (see online version for colours)



In artificial potential field, the direction of the resultant forces is important, unlike the magnitude of them. Thus, we could rewrite the equation (17) as follows:

$$\begin{cases} f_x' = \sum_{k=1}^{N} \left(\mu_o^k . f_{rx}^k + \mu_t^k . \hat{f}_{ax}^k \right) \\ f_y' = \sum_{k=1}^{N} \left(\mu_o^k . \hat{f}_{ry}^k + \mu_t^k . \hat{f}_{ay}^k \right) \end{cases} \tag{18}$$

The direction of the resultant forces could be computed as follows:

$$\theta = \arctan\left(f_y', f_x' \right) \tag{19}$$

From equations (18) and (19), the direction of resultant forces could be obtained as follows:

$$\theta = \arctan\left(\sum_{k=1}^{N} \left(\mu_o^k . \hat{f}_{ry}^k + \mu_t^k . \hat{f}_{ay}^k \right), \sum_{k=1}^{N} \left(\mu_o^k . \hat{f}_{rx}^k + \mu_t^k . \hat{f}_{ax}^k \right) \right) \tag{20}$$

4 Experiments

In order to show the capability and effectiveness of our proposed methods, we applied them to a Nao H25 V4 robot which is produced by Aldebaran Robotics French Company (Gouaillier et al., 2009) (Figure5).

In the experimental phase, robot took an image with 160*120 pixels. We did many experiments but to show the ability of the proposed methods two case studies are investigated here.

Figure 6 is related to Takagi-Sugeno fuzzy type, the target is considered as a virtual point that is given to the robot in the beginning of the process. In the first step, robot decides to move to the target directly because it has not seen the obstacle and feeling only absorption force. When the robot sees the first target in its way, i.e., right obstacle, the distraction force will be added. If the equation (12) is fired to run in the mathematical process, distraction force is so high in comparison with the absorption force that causes to redirect the robot. But, with the help of saturation function, i.e., equation (15), the robot turns only with a limited reliable angle. At this experiment, we choose the robot maximum turning angle about 0.3 radian and therefore, the robot may step and turn 0.3 radian instantaneously. At this state, robot may see both obstacles. The resultant force cause robot prefers to go from the middle of obstacles. In the other words, robot does not go toward the target directly. In fact, we could conclude that the artificial potential fields' direction is affected by the pre-positioned obstacles. After passing all obstacles, the robot goes toward target whereas the saturation function may cause the turning mode happens smoother.

Figure 5 Aldebaran Robotics – NAO H25 V4 (see online version for colours)

Figure 6 Path planning with Takagi-Sugeno fuzzy type (see online version for colours)

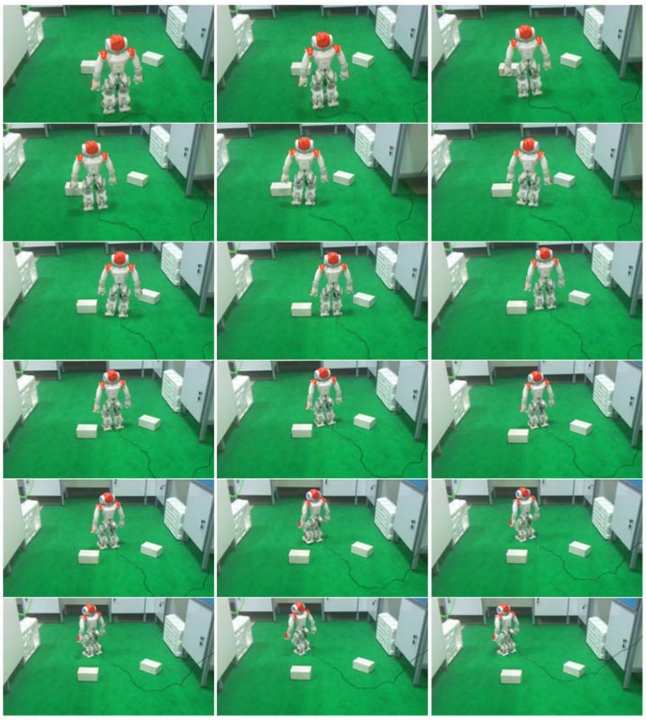


Figure 7 Path planning with Mamdani fuzzy type (see online version for colours)

Figure 7 is related to path planning with Mamdani fuzzy type. The approximation of the target may be given to the mobile robot. In the beginning, the robot could not see the obstacles and the target. Therefore, the robot uses the sub-goal and may move toward the approximated target position. When the robot determines the first target, it may turn instantaneously with stepping according the linguistic rules that is introduced by equation (20). After few steps, the robot could see the obstacle number two. Therefore, linguistic rules may result that the mobile robot moves among the obstacles toward virtual target. Then, robot sees the real target. Now, if robot goes directly to the target it will not collide with obstacles. In the other words, linguistic rules may produce artificial potential fields.

Results showed that the robot could walk to the target without any collisions to the obstacle.

5 Discussion

In this research, a new method which may produce artificial potential field as the natural potential field to apply as the state variable constraints in an online path planning approach based on the data producing by a humanoid robot vision subsystem has been introduced. In the prevalent method of artificial potential field, the absorption force has a direct relation with the distance to the target (Khatib, 1986). Conversely, in our methods and natural potential field, the absorption force has relation with inverse of distance to the target.

Generally, both our proposed method and prevalent methods employing natural potential field, encounter a problem with local minimums. As mentioned later, some researchers have suggested expediting changes in the prevalent artificial potential filed in order to avoid to catching in local minimums. By the way, this strategy may be applied in our proposed method. However, the premier goal of this research is fastened to generate a faster process to develop reliable artificial potential fields, without knowing the exact distance to the obstacles and in order to be applicable to the humanoid robot path planning software.

In the first proposed methodology, we try to produce strong absorption force near the target and weak absorption force when it may be far from the target. Therefore, the mobile robot behaves differently according to its distance to the target. The prevalent method conversely, produces weak absorption force in vicinity of the target and strong absorption force when it is far from the target. Notwithstanding, in our proposed second methodology which employing sub-goal, the moving robot behaves similarly and the decision making process designating the humanoid robot passageway does not affected by distance with the target position.

6 Conclusions

In this paper, two new successful and efficient methodologies have been proposed for real-time path planning process of autonomous humanoid robots in unknown complex environments using the data collecting with the vision sensors to get knowledge about the surroundings. The method of calculating the artificial potential field without having the exact distance and shape of the obstacles was described and demonstrates via some simulations. In the first method, Takagi-Sugeno fuzzy inference system is used whereas in the second one Mamdani fuzzy inference system type is used. Both proposed methods may use box instead of pixel and they use an approximate distance to the obstacles with an admissible degree of uncertainty; thus, unlike other existing approaches, the proposed methods could consider the effect of the process and output noises to handle a reliable walking corridor for the humanoid robot. Also, these methods could use homogeneous meshes that make it simpler, while other methods need non-homogeneous meshes. Generally, the whole locomotion, vision, path planning, motion planning are thus fully autonomous. These results confirm that robot can work in real world situations. These methods need only one camera and are independent of range computing and the principle of superposition may make the algorithms corresponding with these methods very fast. The outputs of the first method are more close to natural potential fields because this method uses a similar function. Unlike traditional artificial potential field, the second method does not encounter any singularity problem, because of using a linguistic method. Moreover, the traditional artificial potential field has a problem with distant of the robot from the target point. In other words, in the traditional artificial potential field based on the fact that the robot is near or far from the target, may show different behaviour. While, the second proposed method in this paper, does not have this problem by using the sub-goal concept.

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