Kicking Motion Planning of Nao Robots Based on CMA-ES

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Abstract: A kicking design motion of humanoid robots is presented in this paper. This kicking design motion uses a gradual accumulation learning method which is based on the Covariance Matrix Adaptation Evolution Strategy (CMA-ES). By planning the best kicking point and the foot space motion trajectory, the first layer of learning optimization can be realized using the linear distance after kicking and the time cost about kicking point as the target. Then, the optimization of the next layer was fulfilled by employing the double balancing mechanism of the robot's center of the gravity and the gyroscope sensor feedback. The learning goal was that the football contact point selection, the weighted penalty of the ankle joint and the performance of kicking were overall considered. The effectiveness of the proposed design method has been revealed in this paper through experimental results.

Key Words: kicking planning, kick, CMA-ES, gradual accumulation

1. INTRODUCTION

The RoboCup3D soccer match is based on the simulator SimSpark. The simulator serves as a standard platform for the soccer robot competition of the RoboCup3D simulation league. The position of football may change at any time in the game. As a result, the robot's kicking trajectory has to be modified in real time to ensure complete and accurate kicking action when the robot dribbles the ball away or gets the position of the ball that may arise at the next moment after a certain prediction by modeling. Key frame insertion method was considered first when the action design issue is involved in the RoboCup research. A set of static joint angles are pre-defined in this kind of methods, and each set of joint angles represents a key frame. The joint position of the robot between any two key frames is obtained by interpolation method. Causing actions implement inflexible is the biggest drawback of this kind of method. Once the action begins to be performed, the robot can not change action strategies based on new information acquired temporarily. Nowadays, in the aspect of kicking motion design, numbers of teams are still using this key frame insertion method [1-4], such as Team HTWK, FC Portugal, B-Human and so on. In addition, Czarnetzki considers leading a balancing mechanism [5] in which a key frame is inserted in Cartesian coordinate system of torso and the true value of the joint angles is calculated by inverse kinematics into the key frame insertion method. In this paper, the kicking planning motion of humanoid robots using a gradual accumulation learning method based on CMA-ES is mainly described.

2. CMA-ES ALGORITHM

The key idea of CMA-ES algorithm is continuously choosing the best local individual to achieve enhances of the population fitness. CMA-ES algorithm not only has the advantages of faster converged rate and rotational invariance, but also can optimize the system efficiently using only a small size of population. There are three specific steps in CMA-ES optimization algorithm as following.

(1) Initial:

Create λ variables randomly, i = 1, 2, ..., λ, to establish the initial population. Initialize the mean of population $m^{(0)}$, step length $\sigma \in R^+$, and evolutional generation g = 0. Initialize evolutional path p_c and conjugate evolutional path p_σ to zero vector respectively.

(2) Repeat:

Create the search population and assume that $y_i^{(g)} \in R^s$ is i-th individual in the n-th generation of the population, the function of CMA-ES to generate offspring individuals is:

$$y_i^{(g)} = m^{(g)} + \sigma^{(g)} z_i^{(g)} \tag{1}$$

Where $z_i^{(g)} \sim N(0, c_i^{(g)})$ i=1, 2, ……, λ, $z_i^{(g)}$ is a r-dimensional random vector generated by a Gaussian function whose mean is zero and variance is $C_i^{(g)} \in R^{n\times n}$. $\sigma^{(g)}$ is the step factor. $m^{(g)}$ is the weighted average of the best μ offspring individuals.

Making a selection and a recombination of the population, updating the mean value of the search population:

$$m^{(g+1)} = \sum_{i=1}^{\mu} \omega_i y_{i\lambda}^{(g)} \tag{2}$$

Recombining $z_i^{(g)}$, selecting the first μ -th $z_{i\lambda}^{(g)}$ in turn, i=1, …… , μ, making:

$$z_{sel}^{(g)} = \sum_{i=1}^{\mu} \omega_i \times z_{i\lambda}^{(g)} \tag{3}$$

Where the weights ω_i are generated in the period of initialization. Meeting $\sum_{i=1}^{\mu} \omega_i = 1$ and $\omega_1 \geq \omega_2 \geq \cdots \geq \omega_\mu > 0$.

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Formula (4) and (5) are used to update search path p_σ and p_c.

$$p_\sigma^{(g+1)}=\left(1-c_\sigma^{g}\right)p_l^{(g)}+\sqrt{c_\sigma^{(g)}\left(2-c_\sigma^{(g)}\right)\mu_{eff}}\,C^{-\frac{1}{2}}z_{sel}^{(g)} \tag{4}$$

$$p_C^{(g+1)}=\left(1-c_C\right)p_C^{(g)}+h_\sigma\sqrt{c_C\left(2-c_C\right)\mu_{eff}}\,z_{sel}^{(g)} \tag{5}$$

Formula (6) and (7) are used to update step length σ and covariance matrix C.

$$\sigma^{(g+1)}=\sigma^{(g)}\times\exp\left(\frac{c_\sigma}{d_\sigma}\left(\frac{\|p_\sigma\|}{E\|N(0,I)\|}-1\right)\right) \tag{6}$$

$$\begin{aligned} c^{(g+1)}=&\left(1-c_{cov}\right)C^{(g)}+\frac{c_{cov}}{\mu_{cov}}\left(p_C p_C^T+\delta\left(h_\sigma\right)C^{(g)}\right)\\ &+c_{cov}\left(1-\frac{1}{\mu_{cov}}\right)\sum_{i=1}^{\mu}z_{i\lambda}z_{i\lambda}^T \end{aligned} \tag{7}$$

(3) Until:

Meeting the convergence condition or the maximum iteration time, which is reached to 200 times. Making η a minimum threshold value which is pre-setted, through judging the objective function namely the fitness function to determine its convergence condition as follow:

$$\max\left(F\left(y_{i\lambda}^{(g)}\right)\right)-\min\left(F\left(y_{i\lambda}^{(g)}\right)\right)\leq\eta, i=1,2\cdots\lambda \tag{8}$$

I.e., the difference between the maximum objective function value and the minimum objective function value of the population sample points should be less than the set threshold value η.

3. KICKING MOTION PLANNING

Progressive accumulated learning method based on CMA-ES is considered conducting in this section. The method is mainly divided into three learning processes, so as to optimize the relevant parameters of a series of kicking actions further. As shown in Fig.1:

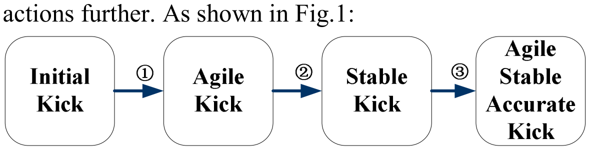


Fig.1. Progressive accumulated optimization process of kick

3.1 Flexible Kick Optimization

(1) Kicking way options:

Far kick means that the ball can be kicked very far one-time. In this way, the robot may not be able to maintain a stable standing posture after the completion of kick and it will be the biggest drawback.

In stable kick, the robot should be ensured to kick as far as possible under the premise of not fall. The completion of the whole action lasts 2 seconds , that is to say, the robot should take this way of kick when the opponent is far away from our player to dribble at least 1.5 meters.

In terms of kicking distance, fast kick is not as good as the two methods mentioned above. But in fast kick, the robot touches the ball less than one second during the completion of the action.

(2) Kicking points

As is shown in Fig.2, the cost of each kicking point is analyzed. A circle is curled with center point the ball and a radius of *ToffsetP*. All the points of the circumference *K1*, *K2……Kn* can be regarded as feasible kicking point. Among them, the cost of kick *kickcost* of several kicking points must be analysed, namely the cost of distance *DistCost* and the cost of turning *TurnCost* are mainly considered, *AgentP* refers to the two-dimensional coordinate value of robot A in relation to the ball, target offset *TOffsetP* refers to the offset of kicking point *K1* in relation to the ball position, the angle α between the current orientation of robot A and the ball, and the angle β between the current orientation of kicking point *K1* and the ball. The cost of distance and the cost of turn make up of *KickCost*. Afterwards, the point of *KickCost* whose value is minimum is selected that is the kick point with the minimum cost. That the cost of *K1* is less than *K2* and other points of the circumference is showed in the figure.

$$\text{DistCost} = \left|\text{AgentP-TOffsetP}\right|/m \tag{9}$$

$$\begin{aligned}\text{TurnCost} &= \left|\text{AgentOri-TargetOri}\right|/360^\circ\\ &= \left|\alpha-\beta\right|/360^\circ\end{aligned} \tag{10}$$

$$\text{KickCost} = \text{DistCost} + \text{TurnCost} \tag{11}$$

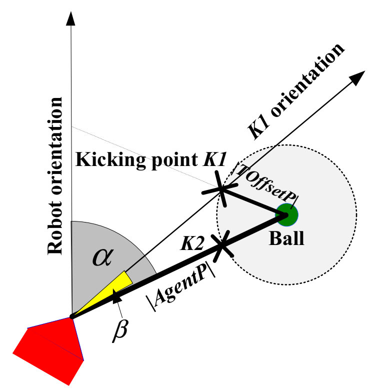


Fig.2.The cost of the kick point

(3) Kicking trajectory planning

The connection point in the trajectory is not guaranteed to be mediate in many application areas. In team Apollo3D, the control of foot kicking motion [6] are realized by using the Bessel function (n = 3):

1) Determining the parameters of the free foot and the Bezier curves. A foot trajectory curve is divided into n points.

2) Calculating the rotation translation matrix of the free foot relative to the hip joint based on the coordinate values of each point in three-dimensional space.

3) Using inverse kinematics to calculate joint angles.

4) Updating the values of joint angles of the robot to maintain its stability.

$$b(t)=\sum_{i=0}^{3}\binom{3}{i}t^i(1-t)^{3-i}P_i \tag{12}$$

In the primary stage of learning, kicking action parameters are set according to knowledge and experience. Generating a basic motion called "Initial Kick". Highly accuracy is the most important aim of the completions of kick motions. So let the robot learns the flexible kicking motions at first. Then let the robot learns how to kick stability and accuracy.

At the first stage, robot only has a simple task: In the stipulated time, positioning the ball and kicking quickly to arrive the most remote distance. The fitness function of the first stage is set as:

$$F_{s1} = Dist_{fward} - Kick_{fall} - Time_{pos}/8.0 \quad (13)$$

In the formula, $Dist_{fward}$ means the most remote distance of ball. $Kick_{fall}$ stands for the falling punishment of robots during the kicking process and the specified value is 1.5. $Time_{pos}$ is the necessary time for robot to find out the kicking point *Ki.* Kicking action planning is vital, but finding out the best kicking point is basis and the value takes the cost of kicking *KickCost* and the cost of time *TimeCost* into account at the same time.

$$Time_{pos} = KickCost/60 + TimeCost \quad (14)$$

3.2 Steady Kick Learning

After the learning of the first stage, robot has got a basic kicking motion. The time to finding a place to kick and the ball movement distance has been greatly improved. On the basis of the first stage learning, stability optimization process is designed which is named as "Stable Kick". The fitness function is:

$$F_{s2} = Dist_{fward} - Kick_{fall} - Time_{pos}/8.0 - Kick_{stab} \quad (15)$$

Where $Kick_{stab} = Bal_{com} + Bal_{gyro}$, namely achieving its stability based on double balanced control mechanism of robot centroid and gyroscope feedback.

3.3 Precise Kick Learning

After observation and analysis, the kicking motion after the stage of "Stable Kick" is found out that it is completed in the long-distance, multi-angle, and wide-range condition. But for a small-angle shot at a close range has some limitations. We make robots learn for precise angle kick motion to achieve a flexible and agile multi-angle kick. During this learning stage, increasing the parameters that the inspection of point of contact at which the robot's foot is in contact with the ball. The penalty is also increased when the threshold of the robot's hip pitch and roll weight is exceeded, which is totally named as $Kick_{var}$. At the same time, adding a reward or punish item r_{task} that can successfully complete the kicking task or not within the limited time. The value stands for the remaining time from completing the task to the recovery of standing posture, and multiplying the deviation value of expect to the target range of the football. The fitness function of this layer can be represented by equation (26) and (27).

$$F_{s3} = Dist_{fward} - Kick_{fall} - Time_{pos}/8.0 - Kick_{stab} - Kick_{var} + r_{task} \quad (26)$$

$$Kick_{var} = \gamma \times q_{AnkRoll} + (1-\gamma) \times q_{AnkPitch} - Kick_{point}/m \quad (27)$$

Where $\gamma(0 \le \gamma \le 1)$ is the weight factor, $q_{AnkRoll}$ means the pitch angular and $q_{AnkPitch}$ means roll angular of the robot's ankle joint, at the same time, the distance difference should be divided by standard value m which between the point of contact and its preset value.

Through the three step-by-step accumulated learning processes, robots can obtain a flexible and stable kick motion. Specific process is shown in Fig.3.

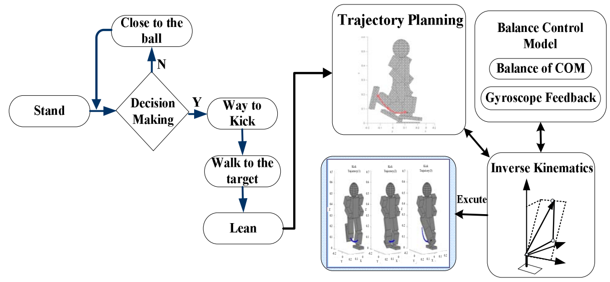


Fig. 3 The kicking flowchart

4. EXPERIMENTS AND RESULTS

The theory of this paper can be verified by simulation through RoboViz and MatLab respectively. All the optimization processes place the ball in the middle of the field. The robot need to walk to the kicking point, to kick the ball to the opponent's goal successfully. And we use 150 samples by 200 iterations based on CMA-ES.

4.1 Experiment 1: Contrast Verification Based on Far Kick

Table. 1. Average kick distance

Time	3.5s	4.5s	5.5s	6.5s	7.5s	8.5s
Before	0m	3.1m	5.2m	9.2m	13.1m	15.1m
After	0m	1.9m	4.1m	7.2m	9.8m	10.9m

The gradual accumulation learning method based on CMA-ES is applied to our team Apollo3D. We experimented in the latest RoboCup3D simulation platform and showed in Roboviz to prove the effectiveness of the proposed design method in this paper. At the same time, this method is contrasted by our old kicking mechanism. In the table we can see that there is a certain advantage ranging from 4.4s to 5.5s in terms of the distance of far kick. From the distance that the ball eventually stops, kicking mechanism with the optimization method described in this paper can score goal from midfield at one-time, and the distance can reach 15.2m. However, the kick way used by the old kicking mechanism furthest reaches only 11.2m.

4.2 Experiment 2: The Contrast Validation of The Curve of Kicking And Optimization Error

Fig.4 is based on particle filtering methods and the comparison charts between the position and orientation error before and after using the kicking optimization method described in this paper. In this chart, the blue curve represents the position choices of the kicking point and the contacting point and the comprehensive error value of the robot's own orientation and the contacting angle's orientation between the foot and the ball in the case of not using any optimization method, while the red curve represents the error value between the position and orientation after using gradual accumulation learning method based on CMA-ES. It is showed in analysis that the positions of kicking point and the contacting point affect kicking flexibility and stability greatly. While the accuracy of shot is directly affected by the robot's orientation and the contacting angle's orientation between the foot and the ball. The figure shows that after three layers of accumulated learning optimization by 200 iterations, the errors of two types are significantly reduced, thus the validity of the learning optimization method is effectively demonstrated.

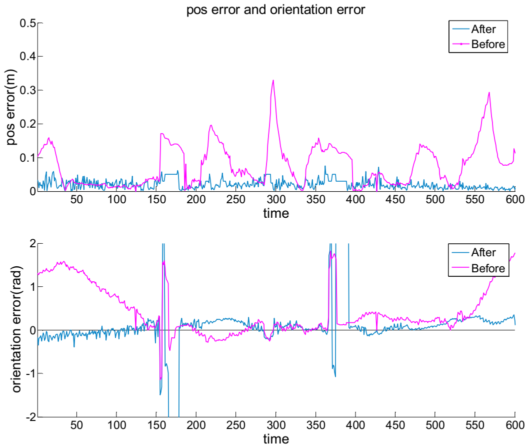
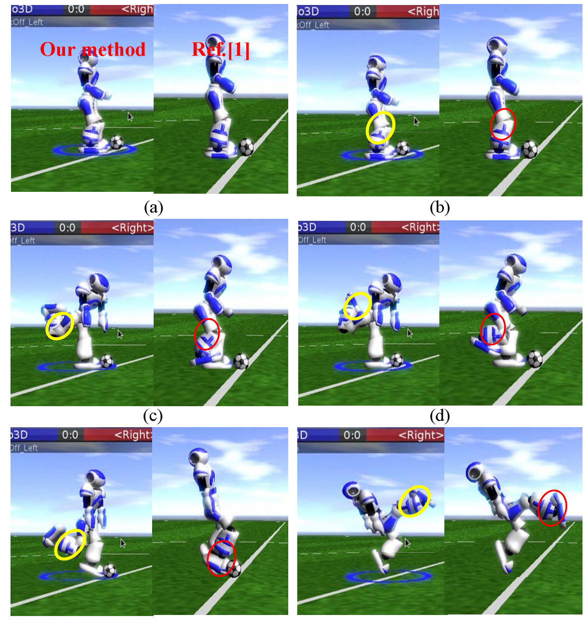


Fig.4.The comparison of error before and after optimization

4.3 Experiment 3: The Contrast Verification of The Kicking Joint Pose Before And After Optimization

Fig.5 shows the transformation of the robot's leg joint pose when the leg lifts back under this two kinds of kicking mechanisms are closely observed. The kicking mechanism under the optimization method described in this paper is used in all the sub graphs on the left side, while fixed point joint parameter optimization method belonging to Portugal team FC Portugal[1] is used in the sub graphs on the right side . Sub graph (a) is No. 2 player's transfer of the center of mass when it stands towards the ball. In sub graph (b), trajectory planning starts to be conducted and the robot lifts its leg back to make each joint to achieve the most appropriate angle. Through observing left yellow signs of all graphs, it is known that the thigh and calf swing back to the most appropriate angle simultaneously and then the ankle twist to tighten foot preparing for kicking, namely successive Knee - Hip - Ankle joint's large angle rotation. However, as to the football team FC Portugal, the player first lifts back the entire leg, then lifts up the calf, finally turns the hip and lifts the entire leg again. As the red logos in the figure, in the kicking process, hesitant repeatedly leg movements will occur and finally the ankle joint cannot be twisted to reach the maximum speed.



(a) (b) (c) (d) (e) (f)

Fig. 5.The comparison of the kick joint poses

5. CONCLUSIONS AND FUTURE WORK

In this paper, a gradual accumulation learning method based on CMA-ES is employed. This method describes from the basic kicking motion to flexible kicking comprehensive. In the end, some conditions like the threshold limits of the contacting point and the ankle joint are added to improve the precision of kicking and to increase the probability of small angle break.

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