Humanoid Soccer Gait Generation and Optimization Using Probability Distribution Models

Changjiu Zhou, Lingyun Hu, Carlos A A Acosta, Pik Kong Yue

Advanced Robotics and Intelligent Control Centre (ARICC)
School of Electrical and Electronic Engineering
Singapore Polytechnic
500 Dover Road, Singapore 139651

{ZhouCJ, HuLingyun, CarlosAcosta, Yue}@sp.edu.sg

***Abstract* – In this paper, humanoid gait generation is formulated as a multi-objective optimization problem with multi-constraint based on probability distribution models. Under this framework, an estimation of distribution algorithm (EDA) based gait optimization approach has been developed to speed up searching in high dimensional coupling space constructed by the permutation of optimization parameters to establish a periodic orbit in biped locomotion. To better understand how information are transferred between these parameters, a factorized distribution algorithm (FDA) based gait optimization method using maximum entropy solution principle has been proposed so that we may progress toward better understanding human locomotion and extend the results to design of humanoid robots. The proposed probability based estimation algorithms have been successfully used to generate and optimize various types of basic soccer-playing humanoid gaits for our humanoid soccer robot Robo-Erectus which has been one of pioneering humanoid soccer-playing robots in the Humanoid League since 2002.**

Index Terms – Humanoid soccer, gait generation and optimization, probability distribution, evolutionary optimization

I. INTRODUCTION

The Humanoid League (HL) made its debut at RoboCup 2002 and has been an interesting highlight of the RoboCup since then. The challenges in this league are different from other leagues. Unlike others, the main challenge in the HL is that of maintaining the dynamic stability of robots while the robots are walking, running, kicking and performing other tasks. Furthermore, the perceptions and biped locomotion of humanoid soccer robots have to be coordinated and be robust enough to deal with challenges from other players. The HL will be the main thrust for the Robocupperes to fulfil their dream of developing a team of fully autonomous humanoid robots that can win against the human world soccer champion team by the year 2050 [7].

2006 is the fifth year running of the HL competition. Tremendous improvements were witnessed in numerous aspects of the participating humanoid robots. Looking at the progress of HL, we could consider 2004 and 2006 to be two critical years in the history of HL in which 2004 was the last year for Humanoid Walk competition and 2006 was the last year for Humanoid Penalty Kick competition. The achievements of HL by 2004 was summarized in Table I [9].

TABLE I
ACHIEVEMENTS OF HUMANOID LEAGUE BY 2004

Technology	Achievements
Perception	The introduction omni-vision system to humanoid robot was obvious in Team Osaka's ViSion robot. Coordination of perception and locomotion was demonstrated in the capability of some robots to perform various actions in response to the environment, be it in the humanoid walk, penalty kick and technical challenge competitions
Communication	Some robots come with wireless communication capability, either in the form of bluetooth or wireless LAN. Multimedia integration was also noticed in some robots
Walk	Ability to walk on uneven terrain was observed in the balancing walk on a slope - a technical challenge conducted for the first time in 2004. Tremendous improvement in the walking speed of the humanoid robots was also observed. The humanoid walk competition record the best time of 50 seconds in 2004, a far cry from the best time of 3 minutes 29 seconds in 2002.
Kick	Striker capability in detecting the ball and changing the direction of kicking in response to the goal keeper's position were noted in the penalty kick competition. Diving capability of the goal keeper to save the goal; both in the ability to change the diving direction in response to the kicking direction of the striker and the ability to stand up again after diving were observed for the first time in 2004 in the penalty kick competition.
Passing	Ball passing capability was observed in the ball passing technical challenge and the demonstration of ball passing between two robots by the team from Osaka University.
Manipulation	Whole body coordination was demonstrated by many robots in their ability to stand up from a lying down position and various dancing and upper body movement demonstration.
Power	Most the robots come equipped with internal power supply.
Materials	The mechanical structure of the robots comes with better design, lighter body (used innovative material like carbon alloy) and sports a more ergonomic look.

Before 2004, the HL competition consisted of three non-game disciplines [15], namely humanoid walk, penalty kick and free style. In additional to the above traditional competitions, technical challenges, including obstacle walk,

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balancing-on-a-slope walk and ball passing, were conducted for the first time at RoboCup 2004. Since 2005, 2 versus 2 soccer game has been implemented [16]. This brought some new technical challenges to HL. Table II shows some of the features of humanoid soccer robots from different fields of technology at RoboCup 2006.

TABLE II
SOME FEATURES OF HUMANOID LEAGUE IN 2006

Technology	Features
Perception	- Omni-vision system, e.g. Team Osaka [19], ROPE - Two-camera system which provides both forward and backward views, e.g. NimbRo [17] - Multi-sensor fusion
Walk	- Omni-directional walk [17,18] - More robust walk [18, 19] - Footrace against four-legged Aibo robots [18]
Kick	- Coordination between perception and kick - Versatile kicking skills, e.g. backheel kick [18]
Passing	- More teams able to perform in passing challenge - Passing in 2 versus 2 game
Cooperative behavior	- Dynamic role assignment - High-level behavior control - Humanoid soccer behaviors

To achieve the final goal of the RoboCup [7], the HL will need to look at the following technical challenges as shown in Table III.

TABLE III
TECHNICAL CHALLENGES FOR THE HUMANOID LEAGUE

Field of Technology	Technical Challenges
Perception	navigation in human environments
Intelligence	task understanding
Cooperative behavior	Cooperative soccer team behaviors
Communication	body and natural language processing
Walk	dynamic walk, jump and run
Kick	kick moving ball, passing
Manipulation	human-like gripping
Power	2 hours rechargeable batteries
Materials	artificial muscle, softer surfaces for robots

Among the above-mentioned technical challenges for HL, how to generate a dynamically stable gait for the humanoid soccer robots with consideration of various constraints is still an important research topic in this area. In this paper, we propose an estimation of distribution algorithm (EDA) based gait optimization approach to speed up searching in high dimensional coupling space constructed by the permutation of optimization parameters to establish a periodic orbit in biped locomotion. Based on the maximum entropy principle, we also develop a factorized distribution algorithm (FDA) based gait optimization method to better understand how information are transferred between these parameters so that we may progress toward better understanding human locomotion and extend the results to design of humanoid robots.

The rest of paper is organized as follows. Biped gait generation and optimization problem formulation is given in Section II. In Section III, two probability-model-based biped gait optimization approaches, namely, EDA and FDA are reviewed. The results by Robo-Erectus is shown in Section IV. Concluding remarks are given in Section V.

II. PROBLEM FORMULATION

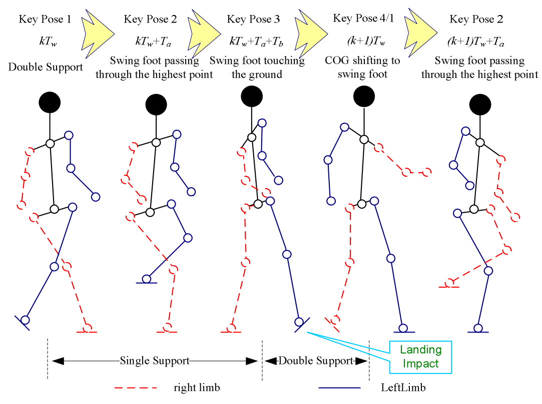

Fig. 1. Key poses of humanoid locomotion

To simplify the biped locomotion model, four key poses are chosen in one complete gait cycle as shown in Fig. 1. Phases between these key poses are approximated by spline functions. Trajectories are typically parameterized as cubic spline function $f_s(\boldsymbol{q},t)$ for joint angles $\boldsymbol{q} \in R^{N_q}$. Therefore, gait generation problem can be reduced to a general nonlinear parametric optimization problem with equality and inequality constraints as:

$$\text{Minimize} \quad f_o(\boldsymbol{q}) = \beta_d f_d(\boldsymbol{q}) + \beta_e f_e(\boldsymbol{q}) \tag{1}$$

$$\text{Subject to} \quad \Omega_i(\boldsymbol{q})$$

Where $f_d(\boldsymbol{q}) = \int_{t=kT_w}^{(k+1)T_w} \Re(\|p_{zmp}(t) - p_{dzmp}(t)\|_2)dt$ stands for ZMP displacement and $f_e(\boldsymbol{q}) = \int_{t=kT_w}^{(k+1)T_w} \|\tau(t)\|_2 \, dt$ is the energy cost during the kth gait cycle. $\Omega_i(\boldsymbol{q})$ are geometric and state constraints.

Two geometric constraints are designed as follows.

$g_1(q)$: position limitations.

$$A_p \le p(q) \le B_p \tag{2}$$

$g_2(q)$: structure limitations.

$$A_q \le q \le B_q \tag{3}$$

Where $p = [p_i(t)]^T$, $A_p = [A_{p_i}(t)]^T$, $B_p = [B_{p_i}(t)]^T$, $p_i(t) = [x_i(t), y_i(t), z_i(t)]$ denotes center position of the ith link at the tth key pose, $i = 1, 2, ..., N_l$, $A_{p_i}(t)$ and $B_{p_i}(t)$ are lower limit and upper limit of $p_i(t)$. $q = [q_i(t)]^T$ stands for the joint angle at the tth key pose, $i = 0, 1, ..., N_l - 1$, $t = 1, ..., N_k$, $N_k = 4$ is the number of key poses, $A_q = [A_{q_i}(t)]^T$, $B_q = [B_{q_i}(t)]^T$, $A_{q_i}(t)$ and $B_{q_i}(t)$ are lower limit and upper limit of $q_i(t)$.

Two more kinds of state constraints including force and velocity constraints are also taken into consideration.

$g_3(q)$: During double support phase, the force on feet must satisfy the force constraint as shown in Equation (4).

$$\sum_{i=1}^{N_l} m_i \ddot{p}_i = f_R + f_L + \sum_{i=1}^{N_l} m_i g \quad (4)$$

Where f_R and f_L are ground reaction force at right and left foot respectively. $\ddot{p}_i$ is the acceleration of the ith link.

$g_4(q)$: Since only the sum $f_R + f_L$ is known during the double support phase, another force constraint is designed with the assumption that internal force f_d in the closed loop structure must be minimized. It can be expressed as Equation (5).

$$f_d = \min\{F(f_R, f_L)\} \quad (5)$$

Where F is the function to calculate the internal force.

$g_5(q)$: Velocity constraint is considered to guarantee motion smoothness with respect to mechanical limitations of the biped system. Such constraints can be simply written as

$$A_{\dot{q}} \le \dot{q} \le B_{\dot{q}} \,. \quad (6)$$

Where $A_{\dot{q}} = [A_{\dot{q}_i}(t)]^T$ and $B_{\dot{q}} = [B_{\dot{q}_i}(t)]^T$ are lower and upper boundaries of the velocity $\dot{q}_i(t)$.

More constraints can be added to achieve more practical requirements for biped gaits generation and optimization.

III. Probability Distribution Model Based Biped Gait Optimization

In this section, we look at how to use estimation of distribution algorithms (EDA) to deal with the multi-model distribution functions appeared in biped gait generation and optimization. We will also explore how to use factorized distribution algorithms (FDA) to build a gait transition model aiming to better understand how information are transferred between parameters so that we may progress toward better understanding human locomotion and extend the results to design of humanoid robots.

A. EDA based Gait Generation and Optimization

For biped gait generation and optimization, there still exist many problems while dealing with the large number of related parameters. Moreover, the parameters to be optimized are interrelated as joint angles are greatly affected by its value at prior key pose. To speed up the searching in high dimensional coupling space, we proposed probability estimation based methods for biped gait generation and optimization. The general structure of the proposed approach can be summarized as follows.

1. **Initialization** Set k=1. Give a multivariate distribution model $Pro(\phi, k)$, j=1,2,…,N_q.
2. **Sampling** Generate N_e samples ϕ_e from $Pro(\phi, k)$ to form the current population $O(k)$.
3. **Selection** Select the N_b best points ϕ_b from ϕ_e according to objective function values. $N_b = \alpha N_s$ ($0 < \alpha < 1$).
4. **Updating** Estimate the marginal probability $Pro^m(\phi_i, k)$ and $Pro^m(q_i, k)$ by the selected best points ϕ_b. Then update $Pro(\phi, k+1)$. i=1, 2, 3.
5. Go back to step 2 if stop condition is not met.

Traditional EDA's performance can be enhanced with two factors[8], namely probability distribution functions and updating rule to cope with the multi-model distribution function appeared in biped gait generation. In our previous works [2-6], several different probability distribution models and updating rules have been proposed (see Table IV).

TABLE IV
PROBABILITY DISTRIBUTION MODELS AND UPDATING RULES

	Probability Distribution Model	Updating Rule
EDA_GP	Gaussian Function	Partial replacing
EDA_SD	Spline Function	Gradient descent
EDA_PP	Parzen Window	Partial replacing
EDA_CPP	Classified Parzen Window	Partial replacing
EDA_PD	Parzen Window	Gradient descent
EDA_Q	Discrete Sampling	Q-learning
EDA_SQ	Spline Function	Q-learning

In the following, we will show how to use spline and Parzen window based probability distribution functions respectively and update probability functions with gradient descent and Q-learning rules.

A1. EDA_S

Different from traditional Gaussian distribution function, the probability model constructed by spline functions describes the probability of variables by a sequence of sample points [4].

Supposing $q_j^i(t)$ is the input degree of joint j at the i^{th} moment in one gait of the t^{th} path input data, then output of this model Pro_j^i can be calculated out by Equations (7) to (9). Where i=1, …, N_{kp}, j=1, …, N_l .

$$v_j^i(t) = \left\lfloor \frac{q_j^i(t)}{\Delta q} + \frac{N_w}{2} \right\rfloor \quad (7)$$

$$u_j^i(t) = \frac{q_j^i(t)}{\Delta q} + \frac{N_w}{2} - v_j^i \quad (8)$$

$$Pro_j^i(t) = F_{j,r_j^i}^i(\cdot) = \sum_{m=0}^{3} Pro_{j,(v_j^i+m)}^i C_{j,m}^i(u_j^i(t)) \quad (9)$$

Equations (7) and (8) implement local parameter computation as indicated before. $\lfloor\ \rfloor$ is the floor operator and the second term in Equation (7) is designed to guarantee $u_j^i(t)$ be always nonnegative. N_w is the number of samples in one kernel function.

The kernel function can be updated by

$$q_{j,(r_j^i+m)}^i(t+1) = q_{j,(r_j^i+m)}^i(t) + \mu_q (D_j^i(t) - F_j^i(t)) C_{i,m}^j(u_j^i(t))$$

Where $D_j^i(t)$ is the desired output of the t^{th} input. μ_q is learning rates for control points. m=0…3, i=1,…, N_{kp} , j=1, …, N_l .

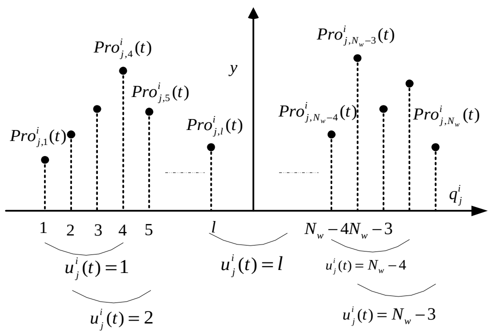

Fig. 2. Spline type kernel function.

A2. EDA_Q

For EDA_Q [5], probability model of joint angles at the first and the third key poses are simply updated with corresponding rewards while transfer probability between these joint angles are updated by Q-learning method.

$$\mathrm{Pro}_{3,3,i} = \mathrm{Pro}_{3,3,i} + \alpha(r(q_{3,i}, q_{1,i})) \tag{10}$$

$$\mathrm{Pro}_{2,3,i} = \mathrm{Pro}_{2,3,i} + \alpha(r(q_{2,i}, q_{3,i}) + \gamma \max \mathrm{Pro}_{3,i} - \mathrm{Pro}_{2,3,i}) \tag{11}$$

$$\mathrm{Pro}_{1,2,i} = \mathrm{Pro}_{1,2,i} + \alpha(r(q_{1,i}, q_{2,i}) + \gamma \max \mathrm{Pro}_{2,3,i} - \mathrm{Pro}_{1,2,i}) \tag{12}$$

$$\mathrm{Pro}_{1,1,i} = \mathrm{Pro}_{1,1,i} + \alpha(r(q_{1,i}, q_{2,i})) \tag{13}$$

Where $q = [q_{1,i}, q_{2,i}, q_{3,i}]$, j, k=1, 2, 3; i=1,2,…,N_q. Reward r is specially designed with the same structure as that in the objective function as shown in Equation (14).

$$r(q_{j,i}, q_{k,i}) = \beta_f r_{local}(q_{j,i}, q_{k,i}) + \beta_g r_{global}(q_{j,i}, q_{k,i}) \tag{14}$$

Where local reward r_{local} deals with energy cost at each actuated joint and it effects mainly on the corresponding joint while the global reward r_{global} is the integral of ZMP displacement between two successive key poses. It is a compound result functioned by all joints. These two parts give an all-around estimation on reward and can provide proper feedback to Q-learning.

$$r_{local}(q_{j,i}, q_{k,i}) = \mathbb{N}\left(\left(\frac{\tau_{j,i} + \tau_{k,i}}{2}\right)^{-1}\right)$$

$$r_{global}(q_{j,i}, q_{k,i}) = \mathbb{N}\left(\left(\int_{t=kp_j}^{kp_j + kp_k} \left\| p_{zmp}(t) - p_{zmp}^d(t) \right\|^2 dt\right)^{-1}\right)$$

A3. EDA_SQ

By combining the spline based kernel function and Q-learning updating rule together, we can formed a new optimization approach called EDA_S_Q [6], which describes evolution as

$$q(t+1) = B^{N_e} \Upsilon R^{N_b} Sq(t) \tag{15}$$

Where $Sq(t)$ defines the spline function based probability distribution of offspring. From this distribution a population of N_e offspring is sampled via random selection R^{N_b} and evaluated by the fitness operator Υ . Proportional to the fitness, a population of N_b parents is selected by the selection method B^{N_e} .

B. FDA based Gait Generation and Optimization

With consideration of the relationship between different joints, a FDA based gait generation and optimization framework has been developed. It defines objective function that satisfies the Factorization Theorem by analysing the biped walking law. Thereby, probability distribution functions can be factorized into conditional and marginal probability functions with the same structure as that in objective function. Since both of these two probability functions can be calculated in polynomial time and conditional distribution function is estimated by limited gait cycles, computation in polynomial time and global convergence are guaranteed in this framework. Moreover, according to the Maximum Entropy Solution Principle, the framework can achieve the maximum entropy solution, which provides a strategy to understand the information transfer and the cooperation relationship between these parameters.

Definition 1 (FDA Based Framework for Biped Gait Generation and Optimization, FFGGO). The proposed framework FFGGO generates and optimizes biped gaits by minimizing the optimization objective function in form of

$$\text{Minimize} \quad f_o(\Phi) = \sum_{j=1}^{N_{k-1}} f_j(\Phi_{j,j+1}) \tag{16}$$

$$\text{Subject to} \quad \Omega_i(\Phi)$$

Preferable permutation solutions of joint angles are obtained by FDA in this framework with Gaussian type probability distribution functions. It possesses following properties as

Proposition 1. This framework FFGGO can approximate the probability distribution of parameter $\boldsymbol{q}$ with the marginal and united probability distributions as

$$pro(\boldsymbol{q}) = \frac{\prod_{i=2}^{N_k} prou_{\cdot,j-1,j}}{\prod_{i=2}^{N_k-1} prom_{\cdot,j}} . \tag{17}$$

Proposition 2. The proposed framework FFGGO is sufficient to converge to global optima in polynomial time $O(N_q N_c \sqrt{N_c})$, Where N_c denotes the number of generations till convergence.

Proposition 3. In the proposed framework FFGGO for biped gait generation and optimization with normal type marginal and united distribution functions, the factorization $pro^{*}(\boldsymbol{q}) = \prod_{i=1}^{N_k} proc(q_{b_i} \mid q_{c_i})$ is the maximum entropy solution

IV. RESULTS

To show the effectiveness of the proposed approach, it is applied to a simulator of the humanoid robot namely Robo-Erectus (RE) as well as the robot itself. The simulation results show that faster and more accurate searching can be achieved to generate preferable biped gait. The gait has been successfully used to drive the RE humanoid robot.

Robo-Erectus is one of the pioneering soccer-playing humanoid robots in the RoboCup Humanoid League (see Fig. 3). The new version of Robo-Erectus as shown in Fig. 4 has been designed to cope with the complexity of a soccer game.

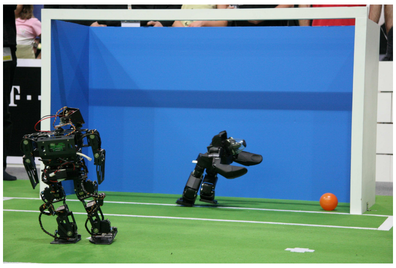

Fig. 3. The striker of Robo Erectus kicking in a goal against the goalie of Team Osaka in RoboCup 2006.

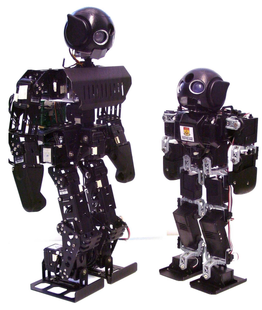

Fig. 4. The new version of Robo-Erectus humanoid robots.

Robo-Erectus is able to perceive different colours and to track them. It also contains a dedicated processor to control the behaviour of the robot, wireless communication with the control PC and the teammates, and a sub-system to control sensors and actuators (see Fig. 5). The heart of the robot is an ARM XScale processor, which is responsible for coordinating the whole system. Connected to the main processor there is a second processor dedicated only to process the vision input. This co-processor improved the performance of the system by permitting the main processor focus only on decisions. Also connected to the main processor, there is a micro-controller responsible for collecting all the values from the sensors and also to send the correct commands to the actuators. The micro-controller deals with all the necessary signal conversion.

The main processor is running Linux as a operating system. Due to the limitations of the system the footprint of the embedded Linux is very small, but yet powerful to permit to take all the advantages of this operating system, such as threading, networking, so forth. Also the great advantages of connectivity are provided by the operating system. The main processor uses wireless LAN to communicate with the workstation and other robots.

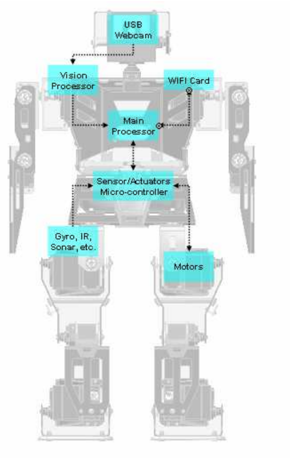

Fig. 5. The Robo-Erectus control system..

The dynamically stable gait generated by the proposed approach is shown in Fig. 6. The performance comparison between EDA_PP, EDA_SP and EDA_GP is illustrated in Fig. 7. We also demonstrate how effect of Q-learning used to update the probability distribution in Fig. 8. The performance of the proposed FDA based biped gait optimization is shown in Fig. 9. The variances of entropy in given in Fig. 10 to show how the information is transferred between different joints.

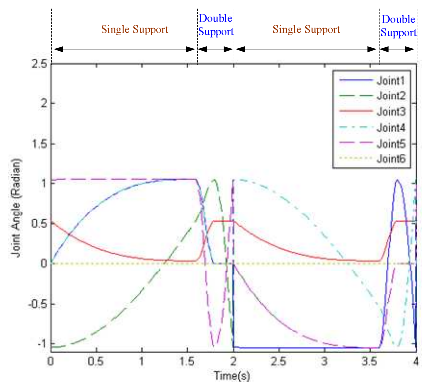

Fig. 6. Gaits generated for Robo-Erectus dynamically-stable walk.

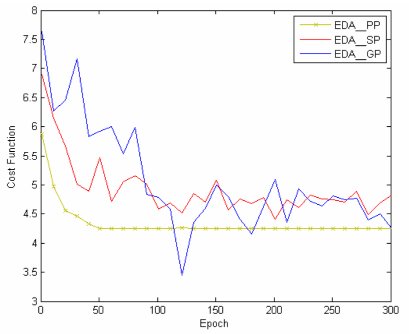

Fig. 7. Performance comparison between EDA_PP, EDA_SP and EDA_GP.

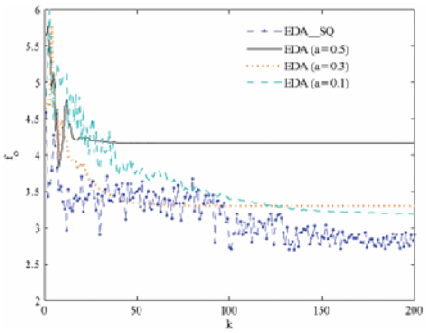

Fig. 8. Performance comparison between EDA_SQ and EDAs with difference updating dates.

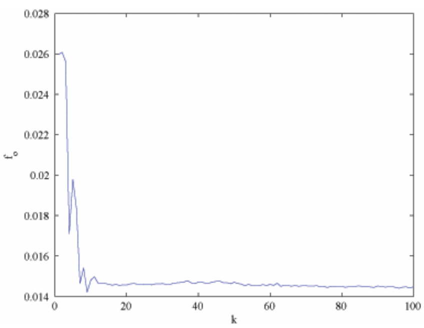

Fig. 9. Performance of FDA-based biped gait optimization .

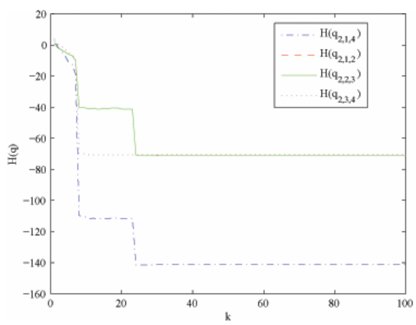

Fig. 10. Entropy changes during FDA-based gait optimization

V. Concluding Remarks

In this paper, both EDA and FDA based humanoid gait generation approaches have been developed in the framework of probability distribution model based optimization. The proposed algorithms have been successfully used to generate and optimize various types of basic soccer-playing humanoid gaits for our humanoid soccer robot Robo-Erectus. The future work will be focusing on to better understand how information are transferred between joints and gait transition aiming toward better understanding human locomotion and extend the results to design of humanoid robots.

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