NomoFC Team Description Paper for RoboCup 2011

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Abstract. We have suggested that a humanoid's quick and stable moving is going to make a robot soccer team strong. In this paper, we describe our efforts to acquire a NAO's gait pattern automatically by using Evolution Strategies. After that we describe a way to improve cognition and decision for playing soccer. Recognizing correct positions of any objects on the soccer field allows NAO to make more smart decision and the smart decision makes NAO more active.

1 Introduction

First of all, we introduce the history of our team "NomoFC" and the origin of the name. In 2006 and 2007, we took part in RoboCup Soccer Simulation League 3D as the team RoboLog3D , because some people of RoboLog3D affiliated to Osaka University from Koblenz University. Since 2008, "NomoFC" has taken part in RoboCup Soccer Simulation League 3D. And the origin of the name of "Nomo" is from our division name that is "**No**nlinear systems, **M**odeling and **O**ptimization group".

Next, we describe our efforts for getting NAO's gait pattern. We have suggested that a humanoid's quick and stable moving is going to make a robot soccer team strong. In this point of view, we are especially focusing on a fast walking skill with NAO model in these years. The purpose of our study is to bring a fast and robust locomotion to 3D simulation robot. However it is hard to realize fast and robust locomotion. So some team has much effort to get their walking skills since we have to build a motion model and adjust many parameters. In our study, a gait pattern is designed by walking parameters which are contained in oscillator, controller and trajectory generator. It means that if we find a suitable parameters for a walking, NAO can acquire a locomotion. Therefore, we have proposed an automatic parameter tuning method, by introducing Evolution Strategies(ES) that is one of Evolutionary Computations. Since it is required that a way to tune the walking parameters effectively and less iteration, we suggest to approaches. The detail of how to tune the walking parameters by using Covariance Matrix Adaptation Evolution Strategies is shown in the section 2.

Then, we describe our team's strategies in order to make our team more strong and have exciting soccer match. Now our team takes a strategy which NAO makes decision based on only a location of the ball object and approach it. It means that NAO ignores the other information about soccer e.g. score, time, location of the other agents and goals. But it is important that NAO recognizes correct positions of any objects on the soccer field and makes decision in order to realize that NAO does not only act more effectively but also makes more smart decision to cooperate with the other team mates. Therefor we must improve three parts, cognition, decision and action. From this point of view, we try to improve cognition and decision in this year. The main idea to improve cognition and decision is applying the other team's world models and strategies. Now we have apply modified Zigorat base world model. However our code does not allow NAO to know where it is on the field by limited vision perception. So we hope that a usage of the other world models makes up this disadvantage and allows NAO to get more multiple information. Then, we focus on that the other teams strategies which have already build to play soccer not only in Soccer Simulation 3D league but also in Soccer Simulation 2D league. So we also hope that a usage of the other team's strategies makes our team strong. The detail of our ideas about team strategies are shown in the section 3.

2 Tuning Walking parameters by using Evolution Strategies

We have dealt with a tuning walking parameters problem as a optimization problem. In this section, we show a walking systems with Central Pattern Generators (CPGs), then we show methods to tune the walking parameters.

2.1 Walking System

Since soccer robots have to move quickly, it is very important problem to acquire fast and robust walking skills. We have applied a central pattern generator to our walking system. A central pattern generator (CPG) is a kind of neural networks in vertebrates. The CPG generates electric pattern for controlling the movement of their body, when they mainly flex their muscle in cyclic motion for example bird's wing stroke, bipedal walking and so on. Thus human being acquires robust walking pattern by using generated patterns from the CPG. Moreover the CPG networks can generate various patterns. It means that the walking system with the CPG has an ability to achieve many motion i.e. changing the direction, pace and so on. From these points of view, we have applied walking system with CPG. In practice, we use a nonlinear oscillator model which is a kind of CPG. In our study, the structure of bipedal walking of NAO is constructed of thre component, CPGs, a foot trajectory generator and joint angle controllers. A trajectory generator designs the joint's positions based on the output pattern from the CPG. Then, the controller has the role to control the each joint angle, based on each

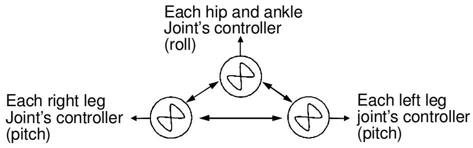

Fig. 1. Phase Oscillators and their connections.

angle generated by trajectory generator. The detail of each component is shown in the following.

We use the phase oscillator model proposed by Tsuchiya et.al. [1] as a CPG model. The generated patterns from phase oscillators control gait and roll motions. The dynamics of phase oscillator is described by

$$\dot{\phi}_i(t) = \omega_i + \sum_{j(j\neq i)}^{3} w_{ij} \sin\left(\phi_j(t) - \phi_i(t) + \delta\theta_{ij}\right), \tag{1}$$

and a diagram of this oscillator network is shown in Fig.1. Where, i is a suffix to indicate the corresponding angle, i.e. $i = 1$ corresponds to rolling motion, $i = 2$ and $i = 3$ correspond to left and right legs, respectively. $\phi_i(t)$ is a phase at time instant t, ω_i and w_{ij} are frequencies and connection weights between oscillators, respectively. The parameters of simplified oscillator networks are as follows.

$$\begin{aligned} \omega_1 = \omega_2 = \omega_3, w_{12} = w_{21}, \\ w_{23} = w_{32}, w_{31} = w_{13}, w_{12} = w_{23}. \end{aligned} \tag{2}$$

Now, we show a control method for each leg joint for generating the gait pattern. Let define the ankle positions $(x_i(t), z_i(t))$, where the origin is center of hip joint, for swing phase,

$$\begin{cases} x_i(t) = \alpha_t \cos(\phi_i(t)) \\ z_i(t) = -H + h \sin(\phi_i(t)) \end{cases} \tag{3}$$

and for support phase,

$$\begin{cases} x_i(t) = \alpha_t \cos(\phi_i(t)) \\ z_i(t) = -H \end{cases} \tag{4}$$

Here, $x_i(t)$ and $z_i(t)$ represent horizontal and vertical position of ankle respectively. The Fig.2 shows geometric model of humanoid legs, here each joint is connected by leg parts.

The attitude of the humanoid robot is defined by H and r at $t = 0$ and $t = 0$ means the time when the humanoid robot starts walking in this paper. The initial conditions of CPG are that

$$\begin{aligned} \phi_1(0) = 0, \phi_2(0) = \pi, \phi_3(0) = 0, \\ \dot{\phi}_1(0) = 0, \dot{\phi}_2(0) = 0, \dot{\phi}_3(0) = 0. \end{aligned} \tag{5}$$

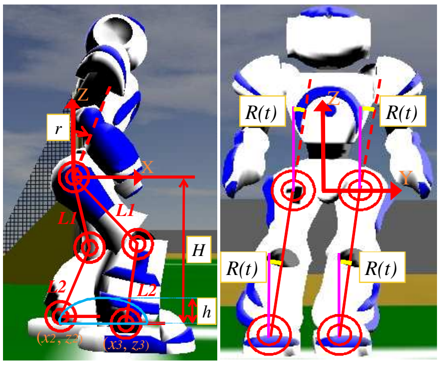

Fig. 2. Trajectory of feet and physical parameters

The humanoid robots bend their hip, knee and ankle joints to adjust the hight of their hip from the ground to H and to adjust the angle of forward tilt to r with satisfying condition of the following equation,

$$\theta_{hip}(t) + \theta_{knee}(t) + \theta_{ankle}(t) = 0. \tag{6}$$

By using inverse kinematics, we can derive target angles of hip, knee and ankle joints, when the hip and ankle positions are decided under the constrained condition equation (6).

Where, α_t indicates the length of the line trajectory given by the following equation,

$$\alpha_t = \min(\alpha_{t-1} + St, \alpha_{max}) \tag{7}$$

where St represents a increment of step size and α_0 means an initial step size. Then, h indicates the length of short axis of the upper half ellipse. H is the hight from grand to hip and r is the angle of forward tilt. $R(t)$ represents a roll angle at time instant t, defined by the following equation

$$R(t) = roll_{max} \sin(\phi_1(t))$$

and the $roll_{max}$ is the maximum value of roll angle given by a prior in consideration with a specification of the robot structure. Finally using PD control scheme, the angle of each leg joint (hip, knee and ankle) are controlled to track the target angle.

Table 1 shows the list of walking parameters and their search ranges. Hear $L1$ is the upper leg length and $L2$ is the lower leg length. In the model of Nao, $L1$ is equal to 0.14 and $L2$ is equal to 0.11. P_{gain} and D_{gain} are the proportional gain and differential gain PD controller. As shown in Table 1 there are twelve parameters in order to make a good locomotion in some scene.

2.2 Parameter Turning

The problem to acquire a gait pattern by using above structures has twelve parameters. A set of walking parameters generates a gait pattern which makes

Table 1. The list of walking parameters

parameters name	min.	max.
$\omega_1 (= \omega_2 = \omega_3)$	2.0	10.0
$w_{12} (= w_{21} = w_{13} = w_{31})$	-1.0	1.0
$w_{23} (= w_{32})$	-1.0	1.0
α_{max}	0.0	$2\sqrt{(L1 + L2)^2 - H^2}$
α_0	0.0	α_{max}
St	0.0	α_{max}
h	0.0	$\frac{L1+L2}{2}$
H	$\frac{L1+L2}{2}$	$L1 + L2$
r	0.0	30.0
$roll_{max}$	0.0	10.0
P_{gain}	0.0	5.0
D_{gain}	-5.0	5.0

the humanoid robot try to walk. However a bad set of walking parameters makes the robot walk slowly or fall down. So it is required to get a suitable set of walking parameters easily and quickly for fast walking skills.

Evolutionary Computation is a powerful tool for searching the optimal solution of various optimization and/or parameter tuning problems. A kind of evolution strategy(ES) [2] can optimize a set of walking parameters by only evaluating a objective performance such as velocity. In applying a ES, how to design the fitness function is important, since the fitness function is only measure the evaluation of objective performance.

Uchitane and Hatanaka defined the fitness function as,

$$fitness = D - |d_l|. \tag{8}$$

In this study, NAO is standing before we evaluate a walking. Then NAO starts walking and we evaluate the walking by measuring distance between staring point to ending point in a short term. Where D is equal to $\sqrt{X_{end}^2 + Y_{end}^2}$ from starting point $(0, 0)$ to ending point (X_{end}, Y_{end}) where a humanoid robot reaches without falling down. We define the direction of the front of NAO's body at starting point is the positive direction of X–axis and the direction of the left of NAO's body is the positive direction of Y–axis. And $|d_l|$ is equal to Y_{end}. This fitness value means that the humanoid robot which is able to walk fast and straight with a set of parameters in time gets a large value and the set of parameters which mark the larger fitness value is better.

In following sections we introduce two approaches to get a well set of walking parameters mask operator applying ES and covariance matrix adaptation evolution strategy.

2.3 Applying CMA–ES

In this numerical examination, we apply "Shark Library" include CMA-ES solver and the library is released at Hansen's homepage. Hansen et al refer the effectiveness of the numbers of μ and λ by applying so called $rank - one - update$ CMA–ES to many benchmark problems and the setting of $\mu = \frac{\lambda}{4}$ shows a better performance [4]. In our problem, the numbers of μ and λ also can affect the performance of parameter tuning. From this point of view, we set the values of μ and λ to $(\mu, \lambda) = (5, 40), (5, 80), (10, 40), (10, 80)$, and consider the effectiveness of the combination of μ and λ. Where "test01_5_40" means the first result under $\mu = 5$ and $\lambda = 40$, and the others means same one.

In the initial generation, we set $\sigma^{(0)} = 0.5$. Then we set 0.5 to a initial values of the average position of parents. It means that 0.5 is the average values of each searching space [0,1]. Thus, the first population has the parameter values which is sampled from $\mathcal{N}(0.5, 0.25)$.

Fig.3, Fig.5, Fig.7 and Fig.9 are the fitness values – generation charts. Their horizontal axis shows the number of generation and vertical axis shows the best value of fitness functin in the generation. Then Fig.4, Fig.6, Fig.8, Fig.10 are the global stepsize – generation charts. Their horizontal axis shows the number of generation and vartival axis shows the square value of global step size σ^2.

In all runs we can not get a set of parameters with which our walking system make the humanoid robot be walking fast. However we can get such a set of parameters in nine runs per twelve runs. In successful runs, we find that the values of fitness function suddenly and quickly increase and the values reach about nine regardless of the combination with μ and λ. Then it seems that the number of generations in which the fitness values starts to rise on $\mu = 5$ is smaller than on $\mu = 10$.

On the other hand, in frailer runs (test02_5_80,test02_5_40,test02_10_80), the value of σ on the first and second case decrease as the number of generation goes but on the other case the value increases. We guess that the searching points reach to around a local optima and they would be trapped into the local optima by decreasing the value of σ. and that the searching points spread over the out range of the searching space by increasing the value of σ.

2.4 Discussion about the Results

In the before section, we show the method to tune the walking parameter and results. In almost result, the values of the fitness function reach about nine by applying CMA-ES. It means that the set of the tuned parameters NAO can walk half length of soccer field in about ten seconds. However a team realizes a faster walking by which NAO can walk the half length of soccer field(the length is nine) in about seven seconds. Since our walking performance in velocity is not enough, our first agenda is to improve the walking system and the tuning methods. Then, our walking can only go straight ahead. The second agenda is to find a way to realize curve walking by using our walking systems.

3 Team Strategies

In this section, we discuss how to improve our team's strategies in this year. In previous years, we have focused on acquiring a quick and stable bipedal locomotion. And our team has taken a strategy which NAO makes decision based on only a location of the ball object and approach it. It is not smart strategies for playing soccer with multi agents. Therefor we will apply a strategies in which NAO recognizes more information to play soccer e.g. location and velocity of agents and ball, score, time and so on, then, NAO makes decision and act by using richer information.

In order to realize such strategies, we will have two improvement our world model and our strategy for decision making. About the former, we hope that a usage of the other world models makes up this disadvantage and allows NAO to get richer information. Now we have apply modified Zigorat base world model. However in our code agents does not know their global position every time with limited vision perception. We will apply the world model of libbats. Of course, we remake a head motion for getting richer information for new world model but this approach allow us to be able to use the other team's smart decision which is build based on libbats world model. We also hope that a usage of the other team's strategies makes our team smart. So we focus on that the other teams have already released smart decision to play soccer not only in Soccer Simulation 3D league but also in Soccer Simulation 2D league. In near future, we will have robot soccer match 11 vs 11 in Soccer Simulation 3D league. Now it is just time to cooperate with Soccer Simulation 2D league.

4 Conclusion

In this paper, we describe our team's history, features and strategies. It is a big goal to realize having soccer match against members of FIFA world championship. Therefor we will improve not only our team but also Soccer Simulation leagues by focusing on the skills which are gotten in the other leagues. At last, we hope that the robocup activity will help people at the time of disasters such as a East Japan big earthquake 2011.

References

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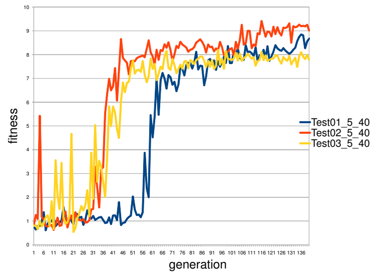

Fig. 3. The values of fitness function with the best solution in $\mu = 5$ and $\lambda = 40$.

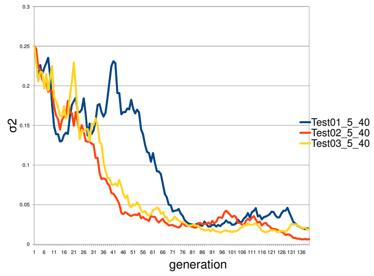

Fig. 4. The values of global step sizes(σ) in $\mu = 5$ and $\lambda = 40$.

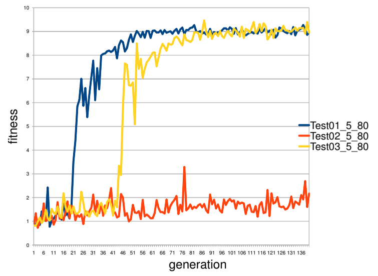

Fig. 5. The values of fitness function with the best solution in $\mu = 5$ and $\lambda = 80$.

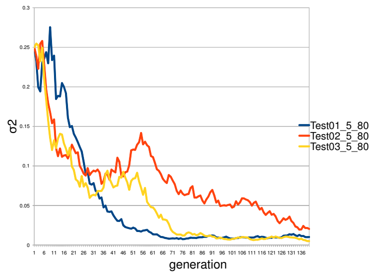

Fig. 6. The values of global step size(σ) with the best solution in $\mu = 5$ and $\lambda = 80$.

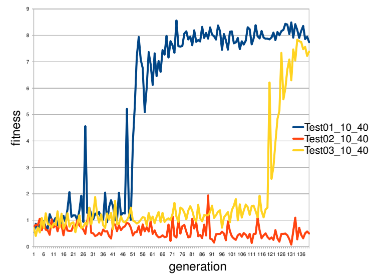

Fig. 7. The values of fitness function with the best solution in $\mu = 10$ and $\lambda = 40$.

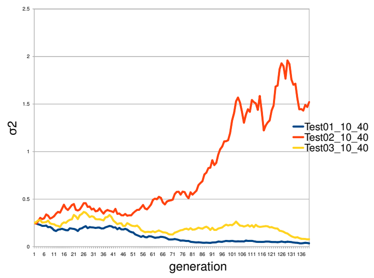

Fig. 8. The values of global step size(σ) with the best solution in $\mu = 10$ and $\lambda = 40$.

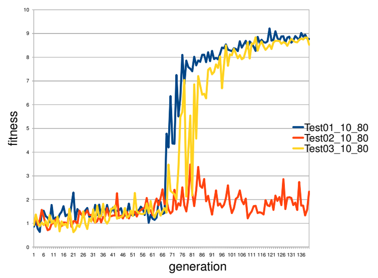

Fig. 9. The values of fitness function with the best solution in $\mu = 10$ and $\lambda = 80$.

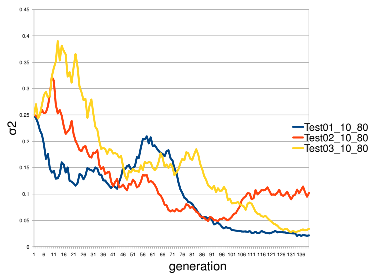

Fig. 10. The values of global step size(σ) with the best solution in $\mu = 10$ and $\lambda = 80$.