1 Team Introduction

CIT 3D team, formerly named CZU 3D from Changzhou Institute of Technology, which was built in 2005, has taken part in several RoboCup competitions. Due to various reasons, we could not participate in RoboCup2009 and RoboCup ChinaOpen2009, but we did not give up the research work in this field. We Won the top 8 place in RoboCup2012, the 2nd place in RoboCup2011, the 4th place in RoboCup2008, the 13th place in RoboCup2006, the top 8 place in Iran Open RoboCup2014, top 8 place in Iran Open RoboCup2013, the 3rd place in Iran Open RoboCup2012, top 16 place in Iran Open RoboCup2011, the 3rd place in RoboCup ChinaOpen2014, the 3rd place in RoboCup ChinaOpen2013, the 3rd place in RoboCup ChinaOpen2012, the 2nd place in RoboCup ChinaOpen 2011, the 5th place in RoboCup ChinaOpen2010, the 3rd place in RoboCup ChinaOpen2008, the 2nd place in RoboCup ChinaOpen 2007, the 12th place in RoboCup ChinaOpen 2006.

In 2014, we published two papers: Research on natural ZMP reference trajectory for biped robot, Shooting method for humanoid robot based on three-mass model. Now we treat RoboCup 3D simulation platform as a algorithm verification platform for biped robot and programming training platform for students. This year, based on the source code of CIT3D2014, we improved the team's performance from two aspects: walking pattern generator with natural ZMP reference trajectory based on preview control, motion optimization based on Particle Swarm Optimization(PSO). All of these are presented in this paper.

2 Walking Pattern Generation with Natural ZMP Reference Trajectory based on Preview Control

In recent years, let biped robot obtain the ability of human-like movement has become a hot topic in the field of robotics . Studies have shown that the ZMP trajectory when human walking is not a fixed point , but the curve moving from the heel to the toe. This year our team achieved human-like biped walking with natural ZMP reference trajectory based on preview control. Preview control has been widely used to generate the biped walking patterns.

In single supporting phase, based on the 3-D linear inverted pendulum model (LIPM) , we can get the dynamical system of biped robot as

$$\frac{d}{dt}\begin{bmatrix} x \\ \dot{x} \\ \ddot{x} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}\begin{bmatrix} \dot{x} \\ \ddot{x} \\ \dddot{x} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} u \qquad (1)$$

$$p = \begin{bmatrix} 1 & 0 & -\frac{z_c}{g} \end{bmatrix} \begin{bmatrix} x \\ \dot{x} \\ \ddot{x} \end{bmatrix} \quad (2)$$

where u = $\dddot{x}$ is the input variable. p is ZMP in x direction. x, $\dot{x}$ and $\ddot{x}$ denotes the position, velocity and acceleration of center of mass (CoM) in x direction. z_c is the height of the plane where the motion of the CoM is constrained. g means gravity. The system of Eq. (1) and (2) can be discretized with a sampling time Δt as

$$\begin{cases} x_{k+1} = Ax_k + bu_k \\ p_k = cx_k \end{cases} \quad (3)$$

where:

$$x_k = \begin{bmatrix} x(k\Delta t) \\ \dot{x}(k\Delta t) \\ \ddot{x}(k\Delta t) \end{bmatrix} \quad (4)$$

$$u_k = u(k\Delta t) \quad (5)$$

$$p_k = p(k\Delta t) \quad (6)$$

$$A \equiv \begin{bmatrix} 1 & \Delta t & \Delta t^2/2 \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{bmatrix} \quad (7)$$

$$b \equiv \begin{bmatrix} \Delta t^3/6 \\ \Delta t^2/2 \\ \Delta t \end{bmatrix} \quad (8)$$

$$c \equiv \begin{bmatrix} 1 & 0 & -z_c/g \end{bmatrix} \quad (9)$$

after given the reference of ZMP p_k^{ref}, the evaluation function is specified as

$$J = \sum_{j=0}^{\infty} \left\{ Q(p_j^{ref} - p_j)^2 + Ru_j^2 \right\} \quad (10)$$

According to the theory of preview control, we can get the control law u_k as follow

$$u_k = -Kx_k + [f_1, f_2, \ldots f_N]\begin{bmatrix} p_{k+1}^{ref} \\ \vdots \\ p_{k+N}^{ref} \end{bmatrix} \quad (11)$$

Where

$$K \equiv (R + b^T Pb)^{-1} b^T PA$$
$$f_i \equiv (R + b^T Pb)^{-1} b^T (A - bK)^{T\cdot(i-1)} c^T Q \quad (12)$$

Matrix P is the solution of the following Riccati equation:

$$P = A^T PA + c^T Qc - A^T Pb(R + b^T Pb)^{-1} b^T PA \quad (13)$$

Based on the above formulas, we chose the following parameters to apply to NAO robot: $z_c = 0.24m$, $g = 9.8 m/s^2$, $\Delta t = 0.02s$, $N = 200$, $Q = 1$, $R = 0.00000001$. After setting ZMP reference trajectory as straight line, we can get the ZMP reference trajectory, actual ZMP reference trajectory and actual CoM trajectory shown in Fig. 1. Fig. 2 show some actual walking scene based on preview control in RoboCup rcssserver3d.

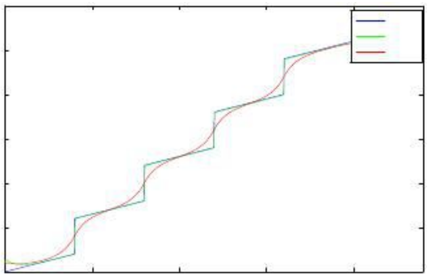

Fig. 1. ZMP and CoM trajectory based preview control

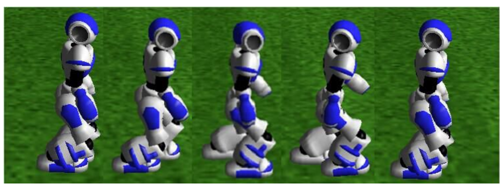

Fig. 2. walking scene based preview control

3 Localization and Noise Reduction Method

There are a variety of methods of robot localization under perfect visual, for example: gyroscope positioning, a sign pole position, three sign pole position. In accordance with it, CIT3D soccer simulation uses a gyroscope positioning combining with a sign pole position and three sign pole position under the restricted visual. These different methods are integrated in a structure whice can see from the fig.3. Next we introduce the details of these methods.

```
Input:msg_vision  //Visual information coming from the server
Output:      //Position and orientation of the robot itself
Parse(msg_vision) →  num_flag //Saw the number of sign posts
Switch num_flag
{ case ‘ 0’ :
gyroscope positioning LocWithGyro → , ;break;
case ‘ 3’ :
three sign pole position LocWithThreeFlag → , ;break;
Default:
 a sign pole position LocWithOneFlag → ,;break;}
```

Fig3 the method under the restricted visual

Gyroscope positioning:This method is relatively simple , local information that get from the gyroscope will be converted to information of the global coordinate system. Then these information is directly used to calculate the position. Meanwhile, these information will be pretreated to get a estimated value of direction through world model, Then we would get the result that a estimated value of direction subtract the known location of the corresponding.

a sign pole position:when the robot only see a flag pole, We assume that this flag pole position is P_{vision} in the Robot vision, which is a relative distance vector. P_{flag} is the global coordinate sign posts. According to the formula (14), we can calculate the global coordinates of the robot.

$$P_{robot} = P_{flag} - R_{robot} P_{vision} \tag{14}$$

Three sign pole position:If we know the global coordinates of three sign posts, (x_1, y_1, z_1), (x_2, y_2, z_2), (x_3, y_3, z_3), and Their distance from the robot's perspective, d_1, d_2, d_3, We will extract the ternary quadratic group According to the formula (15).

$$\begin{aligned}
&(x-x_1)^2+(y-y_1)^2+(z-z_1)^2=d_1^2\\
&(x-x_2)^2+(y-y_2)^2+(z-z_2)^2=d_2^2\\
&(x-x_3)^2+(y-y_2)^2+(z-z_2)^2=d_2^2
\end{aligned} \tag{15}$$

According to the principle of the local coordinate system and homogeneous transformation in the robotics,We can get the following equations:

$$p_{flag} = p + R\,p_{rel} \tag{16}$$

$$R = \begin{bmatrix} p_{flag1} - p \\ p_{flag2} - p \\ p_{flag3} - p \end{bmatrix} \begin{bmatrix} p_{rel1} \\ p_{rel2} \\ p_{rel3} \end{bmatrix}^{-1} \tag{17}$$

According to equations,we can get the head posture of robot.Through each part of the homogeneous transformation matrix, we can also get the rest of the body posture of robot.

4 Motion Optimization Based on PSO

As we all know, a stable and flexible bipedal walk is always the key whether the humanoid robot can complete the task smoothly and quickly or not. To get such walking gait by machine learning method, Particle swarm optimization(pso) is presented,which was developed by Kennedy and Eberhart in 1995,has been widely applied to different fields such as multi-objective optimization, data classification,data clustering, signal processing, robot path planning and so on.In the learning process,we should iterate N times and evaluate the optimal value each time by using PSO algorithm ,then we' ll get a series of optimal parameters.Following is the evaluation function of walking gait optimization.Fig.4 show the best fitness during the iterative process .Obviously,the least evaluation value is the best one.Finally,we can get a series of parameters.The we will go on the next iteration on the basis of the last time,According to the formula of PSO algorithm.what we do is let one robot to perform machine learning ,however, the results are sometimes a local optimum rather than a global optimal.So at the next step,we will run the 11 players at the same time which can exchange the information according to the algorithm of PSO.

Algorithm 1 evaluation function

```
Float walk::GetCost()
{
Float Cost=0;
If(startPos.x()>endPosx()){
Cost=0;
```

```
Return(Cost);
}
Cost=startPos.getDistanceTo(endPos);
If(addFallDownPunish && fallDown){
Cost-=fallDownPunishment;
}
If(addBodyVariancePunish)   //increased punishment if the body of robot sway too much
{
Cost-=bodyVariancePunishment;
}
Return(-Cost);
}
```

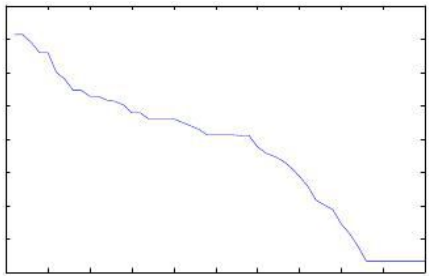

Fig. 4. the iterative process