Abstract. This paper describes the improvements of ZjuNlict we have made during last year. A concave kicking and horizontal dribbling bar are designed for our mechanical system. With respect to the electronics system, the power system and motor driver are redesigned and implemented. The frame rate of the software system is doubled from 30Hz to 60Hz. A neural network is used for compensating robot’s open loop control.

1 Introduction

Our team is an open project supported by the National Lab. of Industrial Control Technology in Zhejiang University, China. We started since 2003 and participated in RoboCup 2004 and RoboCup 2005. The competition and communication in RoboCup games benefit us a lot, We have grown to be one of the best teams in China.

2 Mechanical Design

Our new robots’ mechanical information:

– Height: 145mm
– Diameter: 178mm
– Percentage of ball coverage: 18%

With regard to some problems we have encountered in Osaka, some improvements have been made to our mechanical system especially on dribbling and shooting devices. After lots of experiments on the materials using in the horizontal bar, we finally chose one kind of soft rubber tube which can dribble the ball stably. The material also has a good damping property which can improve the stability of passing ball. We also designed a new tracking rail and a concave shooting surface to improve our shoot device’s accuracy.
3 Electronics

After RoboCup 2005, our members of Electronics system have made great improvements to our power system, motor driver, and a new charge/discharge circuit to support our new shooter. We replaced the ordinary liquid electrolyte lithium-ion battery (LIB) used before with new Polymer Lithium-Ion Battery (PLB) which can produce high current when required. A better MOSFET IC from IRF Corporation will be used in our new design, with a feature of lower channel resistance, higher current capacity, and more power to DC motors. As for the charger, new circuit is able to charge two 22000µF capacitors up to 90V within 20 seconds, which is nearly nine times faster than former circuit could do.

4 Vision System

We use two Basler A311fc Fireware cameras, one for each half-field. The image data is sent through 1394 FireWire to computer in RGGB format, then changed to HSI color space for recognition. This year we increase our frame rate from 30HZ to 60HZ.

To minimize the noise, we first take an image without any objects in it as the background image. Then during the period of procession, we compare current image with it, with a result of difference in the image, on which we base in the steps below. For connecting regions, we use verge searching, and then filtering noises by size. We decide the number and the angle of each robot by the angles between their ID patch. We use Tsai’s method [1] to do our calibration, and the mistake is under 10mm.

5 Motion Control

Because of the inherent mechanical characteristics, there are variations between the command (|V|, θ, V\_\text{rotate}) we send to the robot and the result gotten from the execution. These variations are critical in robot motion control. We train a three-layer feed-forward neural network to model the variations, and calculate the compensation we should modify the commands sent to the robots.

As for omni-wheels robot, the translation movement and the rotation movement are independent. This means that they can be compensated respectively.

We train the neural network in this way: Certain commands (|V|, θ, V\_\text{rotate}) are sent to the robot, we get the vectors (|V'|, θ', V\_\text{rotate}') which robot really executes by measuring the vision logs. For these given commands (|V|, θ, V\_\text{rotate}): 

- |V| varies between 0cm/s and 200cm/s with a step of 20cm/s
- θ varies between 0° and 350° with a step of 10°
- V\_\text{rotate} = 0

The neural network’s input vector is (|V|, θ), output vector is (|V'|, θ', V\_\text{rotate}') and the hidden layer have 5 neurons. We use the data set gotten in previous
measurement to train the network. When the train finished, we get a neural network which can compensate any given command($|V|, \theta$).

We also measure the rotate velocity $V_{\text{rotate}}$ compensation by send commands which $V_{\text{rotate}}$ varies between 0 rad/s to 10 rad/s with a step of 1 rad/s and $|V| = 0$. The result show that the Coefficient $\lambda$ of compensation for rotate velocity is nearly a constant. ($\lambda = V_{\text{rotate}}/V_{\text{rotate}}$). The compensation of rotate velocity $V_{\text{rotate}}$ can be obtained through following equation:

$$V_{\text{rotate}}'' = \lambda \cdot V_{\text{rotate}}' + V_{\text{rotate}}'$$

$V_{\text{rotate}}'$ is gotten by the neural network.

You can refer to a more detailed method in bibliography [2].

6 AI Module

6.1 Plays

Our A.I. module is implemented using a play-based approach. Each play represents a fixed team plan, in which each team member has a role to perform and that role may have variable skills to execute. The plays can transfer to each other, and the role for each robot can change too. We employ artificial potential field [3],[4] to complete such transfer.

6.2 Skills

Skills are executed independently for each robot in the team. They are actually the highest level of a single robot behavior, which includes shoot, pass, goalie, etc. For one specific skill, the destination information for robot is calculated, which includes destinate positions, the statuses of kicker, dribbler.

References