The RoboCup-NAIST: A Cheap Multisensor-Based Mobile Robot with On-Line Visual Learning Capability

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Abstract. Our contribution is composed of two parts: one is development of a cheap multisensor-based mobile robot, the other is development of robust visual tracking system with on-line visual learning capability. To promote robotic soccer research, we need a low cost and portable robot with some sensors and a communication device. To date, there is no platform for robotic soccer. Therefore, each researcher must build his own robots or utilize robots which are commercially available. This paper describes how to construct a robot system which includes a lightweight and low cost mobile robot with visual, tactile sensors, TCP/IP communication device, and portable PC where Linux is running. In real world, robust color segmentation is a tough problem because color signlas are very sensitive to the slight changes of lighting conditions. In order to keep visual tracking systems with color segmentation technique running in real environment, on-line learning method for acquiring models for image segmentation should be developed. In this paper, we also describe an on-line visual learning method for color image segmentation and object tracking in dynamic environment. An example of the developed soccer robot system and preliminary experimental results are also shown.
Keywords: Multisensor-Based, Portable PC, Linux, On-line Visual Learning, Color Image Segmentation and Tracking

1 Introduction

Robotic soccer is a new common task for artificial intelligence (AI) and robotics research[2, 3]. The robotic soccer provides a good testbed for evaluation of various theories, algorithms, and agent architectures. Through the research for accomplishing this task, a number of technical breakthroughs for AI and robotics are expected to be discovered. We focus on two points among RoboCup physical agent challenges [3]: one is **platform** and the other is **perception**.

So far, many researchers have been studying robotic soccer and have proposed a variety of theories and methods for controlling, planning and so on. They built a team of robotic platforms for playing soccer by themselves, or purchased robotic platforms (for example, [4]). There is no standard robotic platform design for robot soccer. Generally, contemporary robotic systems involve large amounts of expensive, special purpose hardware for motor control and image processing.

In this paper, we describe how to construct a cheap multisensor-based mobile robot and its control system mainly made from a state-of-the-art portable PC, a battery-powered R/C model car, a CCD camera and a set of tactile sensors. Since recent portable PC is affordable and powerful, such a PC is used as a central controller which manages processing sensor information, controlling motor and communication between robots. As a chassis of the mobile robot, a 4-wheel drive, R/C model car is utilized. The important feature of our robot is that this platform has all its essential capabilities on board. Our platform consists of driving, visual sensing, tactile sensing, motor control, communication and decision-making system. Since each system is made of devices commercially obtainable, we can reduce both of the cost and complexity of the system. According to our design principle for soccer robot system, those who are interested in the robotic soccer would easily utilize or build this robotic platform by themselves.

In real world, robust color segmentation is a tough problem because color signlas are very sensitive to the slight changes of lighting conditions. Currently, human programmer adjusts parameters used in discriminating colored objects in response to the changes of surroundings. In order to keep visual tracking systems with color segmentation technique running in real environment, on-line learning method for acquiring models for image segmentation should be developed. In this paper, we also proposes an on-line visual learning method for color image segmentation and object tracking in dynamic environment. To realize on-line learning, our method utilizes fuzzy ART model [5] which is a kind of neural network for competitive learning. The mechanism of this neural network is suitable for on-line learning and different from that of backpropagation type neural network. Color image we deal with is represented by YUV color space. Although YUV space well reflects the human eye's response to color, YUV space is not suitable for inputs of fuzzy ART model. For this reason, our method transforms YUV space to a particular color space which is linearly separable using only plance parallel to the principle axes.

To evaluate the developed system, we have implemented some behaviors for playing soccer and a modified fuzzy ART model for on-line visual learning which can perform color image segmentation and object tracking. Preliminary experimental result are also shown.

2 Our Hardware Architecture

In order that our soccer robots are used by not only roboticists but also researchers in other research communities, our soccer robots should be manageable. Furthermore, in order that our robot system satisfies the requirements of a standard platforms, it is important to reduce the cost and time for building our robot system. To address this issue, we use a portable PC as a central controller of robot system which is recently affordable and powerful.

2.1 Driving System

As a chassis of the mobile robot, we utilize a 4-wheel drive, R/C model car which is commercially available. Actually, we utilize a chassis of "BLACK BEAST" (NIKKOH [1]) (See **Fig.**1). This chassis is composed of a PWS (Power Wheeled Steering) system with two independent motors. Because of this mechanical structure, our robot can rotate at the same place. This system is useful for avoiding

[1] NIKKOH is a Japanese toy company. BLACK BEAST is also commercially available outside of Japan.

the situation that its body gets stuck into corners. Existing motors provided by NIKKOH are comparratively powerful. However, if we put something whose weight is more than 4 Kg on the existing chassis, the body can't move around by those motors. In such case, we can change existing motors to high-torque motors (TAMIYA RS-540 Sport Tuned Motor). As a result, even if we put something whose weight is about 4kg on our robot, our robot can move around.

2.2 Tactile Sensing System

A tactile sensing system is used for detecting contact with the other objects such as a ball, teammates, opponents and a wall. It is also important to have tactile sensing capability in the soccer robots, because soccer robots frequently collide with each other, walls or a ball in a soccer field. Furthermore, tactile sensing system can compensates for limitation of visual sensing. Since the field of view of the camera mounted on the robot is limited, if collision between the robots or between the robot and the wall or the ball occurs on the outside of the field of view, it is difficult to detect these happenings based on the image information. Tactile sensing system where tactile sensors are set around the body of soccer robot is very useful for solving this problem. Since the cost of producing a tactile sensing system is generally high, this prevents it being used widely.

Here, we construct a cheap tactile sensing system (See **Fig.**2) by remodeling a keyboard which is usually used as an input device for PC. A keyboard consists of a set of tactile sensors each of which is a ON/OFF switch called a key. If a key is pressed, the switch is ON. If not, the switch is OFF. Since we can get a keyboard at a low price, it is possible to construct this tactile sensing system for soccer robots at a low cost.

If a tactile sensor (key) hits an object such as a ball or an opponent, the sensor outputs an ASCII code corresponding to the key. In case several sensors have contact with the other object, an output of this sensing system is a sequence of ASCII codes.

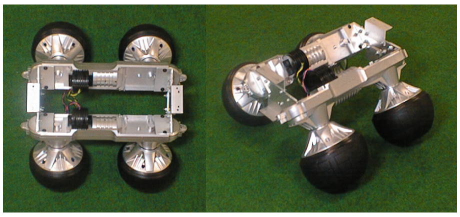


Fig. 1. Our driving system.

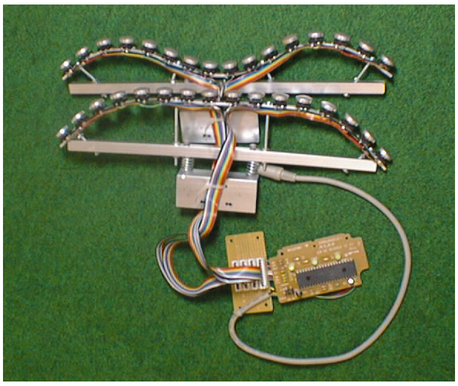


Fig. 2. Our tactile sensors made of a key board.

2.3 Visual Sensing System

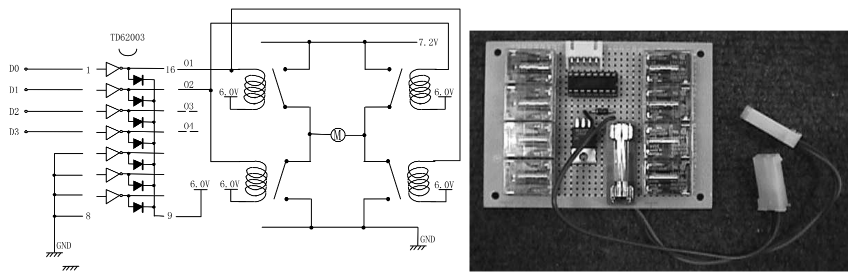
Our robotic soccer project aims the development of robotic soccer players with on-board visual sensor like human soccer players. So, a visual sensing system in our soccer robot plays a fundamental role in acquiring visual information and recognizing it. Our soccer robots make a pass or tackle and shoot a ball into a goal based on the images taken by the on-board camera. In order to build such visual sensing system, we have chosen to use a commercial video capture PCMCIA card (IBM Smart Capture Card II, hereafter SCCII) which can be easily plugged into a portable PC and a color CCD camera (SONY EVI D30, hereafter EVI-D30) which has a motorized pan-tilt unit.

SCCII is a PCMCIA type-II video capture card which can capture at 30 frame-per-second at maximum resolution 320-by-240 in 16-bit RGB formats . We can feed video to SCCII in NTSC or PAL format, and the card provides jacks for both composite-video and S-Video input. A device driver for the use of SCCII on Linux OS[1] is distributed as a free software. We utilize this device driver in order to capture images on Linux OS.

EVI-D30 is a high-performance color CCD camera, because it has auto target tracking function based on color information and motion detection function. We can control eyes of EVI-D30 with a motorized pan-tilt device which can be managed by a portable PC through RS232C. The pan and tilt angle of this device ranges from -100 to $+100$ and from -25 to $+25$, respectively. In this way, this camera can cover wide field of view. Since our soccer robot has such sensing capability, our robot can find a ball by moving its camera head without moving its body.

2.4 Motor Control System

A motor control system is used for driving two DC motors and is actually an interface board between a portable PC and motors on the chassis of our soccer robot (see **Fig.**3). This control board is plugged into a parallel port on the portable PC. Our motor control system manages only the direction of current to a DC motor. The control circuit in this board consists of mainly 4 relays in terms of one motor (see **Fig.**3). These relays are used as just like an ON/OFF switch and for controlling the direction of current. This board is powered by a 7.2 V battery for a R/C model car. As a result, this board can sends three control commands to right and left motors such as "(Forward, Stop, Backward)". The motor control command is actually 2 bits binary commands for one motor. Therefore, totally 4 bits (D0!&D1 or D2!&D3 in **Fig.**3) in the parallel port are used for transmitting motor commands to the control board. Since we can send the motor control command to each of the two motors separately, our soccer robot has 3 sub-action primitives, forward, stop and backward in term of one motor. All together, our soccer robot can take 9 action primitives.



(a) (b)

Fig. 3. Our motor drive board.

2.5 Communication System

In the soccer game, teammates need to communicate each other for accomplishing a given task in cooperative manner. So, we set a wireless LAN device for communication on our soccer robot. The wireless LAN device is actually WaveLAN(AT&T) which can be plugged into a portable PC. The system operates in 2.4GHz frequency band. The rate of transmitting data is 2Mbps. The maximum transmission range will reach several hundred meters when there is a clear line of sight between the transmitter and receiver.

2.6 Intelligent Control System

We call a central controller for processing sensor information and controlling the body of mobile robot and camera "intelligent control system". The intelligent control system consists of software, programming environment and OS. In order to adopt an OS as the central manager of robotic system, the OS should have some characteristics as follows:(1)It is possible to run multiple independent processes. (2)It is possible to make a process abort or wait for running again. (3)The system provides mechanisms for simple and high-speed process synchronization and communication.

In this work, we have chosen to use Linux OS as an OS for intelligent control system. Linux is a freely-distributable, independent UNIX-like OS. Much of the software available for Linux is developed by the Free Software Foundation's GNU project. It supports a wide range of software, including X Windows, Emacs, TCP/IP networking (including SLIP/PPP/ISDN). Linux has become a cost-effective alternative to expensive UNIX systems. Linux is being used today by hundreds of thousands of people all over the world.

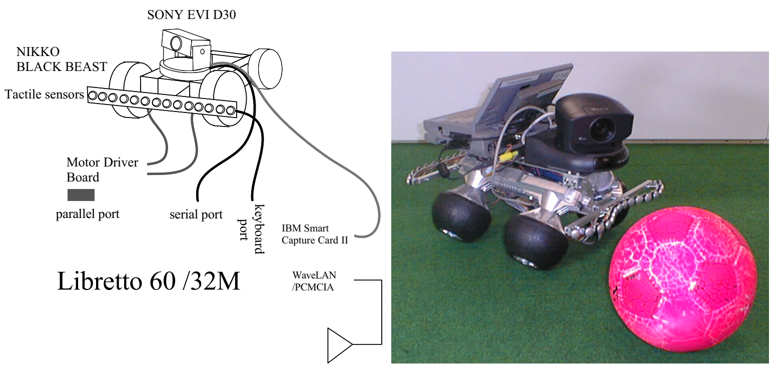
We cannot guarantee user-mode processes to have exact control of timing because of the multi-tasking nature of Linux. Our process might be scheduled out at any time for anything from about 10 milliseconds to a few seconds (on a system with very high load). However, for most applications in RoboCup competition so far, this does not seem to really matter. If we want more precise timing than normal user-mode processes, there is a special kernel RT-Linux that supports hard real time(See [6] for more information on this.).

3 System Configuration of Our Soccer Robot

Currently, we have developed a vision-based mobile robot for robotics soccer as shown in **Fig.**4. As a portable PC, we have chosen to use a Libretto 60 (Toshiba) which is small and light-weight PC. The total cost of this soccer robot is about $ 4,800.

4 Our Software Architecture

In order to control our hardware systems, we use a shared memory [7] and 5 software components which are the motor controller, camera controller, tactile sensor module, vision module and behavior generator. **Fig.**5 shows an interactions between these software components. Note that this figure shows the software architecture of our current robotic soccer system. All software components read and write the same shared memory. Using this shared memory, they can communicates each other unsynchronously. As shown in **Fig.**5, we define the structure of the shared memory. For example, the behavior generator takes the state of camera, vision, tactile and motor in the shared memory as input vectors.



(a) (b)

Fig. 4. Our soccer robot.

Then, it combines these information with programmer's knowledge and decides the robot's action at next time step. Finally, it writes the motor command for the motor controller on the shared memory. In the same way, other software components read states and write commands in each timing.

4.1 Motor Controller

We assume that a motor command is defined by a action primitive and its duration. In our robotic system, an action consists of a combination of 4 action primitives (move forward, backward, turn left, and turn right) and 4 kinds of the duration ($100msec$, $150msec$, $200msec$, $300msec$). Furthermore, we add one action for kicking a ball strongly to the actions. This action is produced by a combination of "move forward" and $500msec$ duration. Totally, our mobile robots can take 17 actions. Motor controller module reads the command from the shared memory every $100msec$. If there is a command, it execute the command and rewrite the executed command as the state of motor.

4.2 Camera Controller

We can control the on-board camera (SONY EVI-D30) through RS232C with the VISCA protocol provided by Sony Corp. Using VISCA, we can control the pan and tilt angle, the focal length of the camera and take its focus. Furthermore, we can turn on and off the camera through this protocol. In robotic soccer task, panning the camera is important action for tracking the objects such as a ball, a goal, teammates and opponents. Since the soccer robots frequently lose the ball in the field, they must find the ball again as soon as possible. We think panning the camera is very useful in order to realize the procedure for finding a ball called "finding behavior". We implement the finding behavior as follows:

repeat
 Read the state of ball from the shared memory
 Make the camera rotate by 30 !,
until the ball is in view

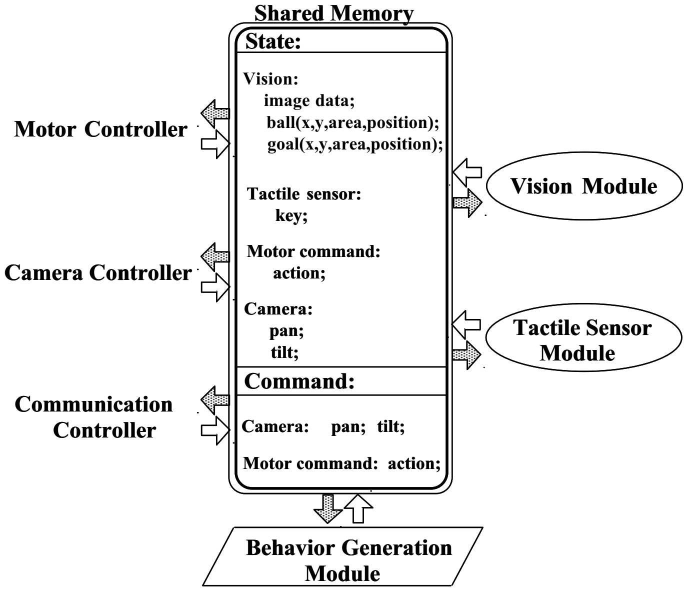


Fig. 5. Software architecture.

4.3 Tactile Sensor Module

Since our tactile sensor system is actually a keyboard, an output of the sensor system is an ASCII code corresponding to the key. We can get this ASCII code via X Event [8] which is a library function of X11 for detecting all events in X Window system. Our tactile sensor module maintains a table of ASCII codes and the configuration of tactile sensors. Each tactile sensor is numbered 1 to 32 so that the left front of tactile sensor unit might be numbered 1 and the right back 32. In case a sensor have contact with an object, the sensor module can detect which sensor have contact with the object using the table that shows corresponding between ASCII codes and the index number of tactile sensors. Then, the tactile sensor module rewrites the index number of the detected sensor as the state of the tactile sensor system on the shared memory.

4.4 Vision Module

The vision module provides some information about the ball and goal in the image. To date, in RoboCup competition, each soccer robot tried to discriminate such objects based on color information. In our study, we also use color information for segmenting and tracking objects (a ball, goals, white lines, teammates and opponents). Furthermore, in order that such color image segmentation and object tracking should be correct even if surroundings such as lighting condition changes, our vision module has on-line visual learning capability based on fuzzy ART model[5]. After the color segmentation, we calculate the coordinates of the center of ball and goal position, and the both maximum and minimum horizontal coordinates of the goal and so on. (See **Fig.**5.) Then, based on segmented regions, our robots perform visual tracking. Our vision module also discriminates in which position center of ball or goal appears among three positions (right, center and left of an image).

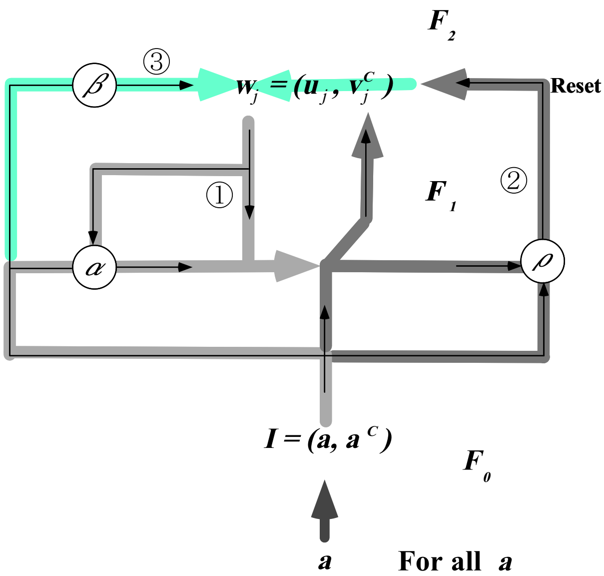


Fig. 6. Fuzzy ART architecture.

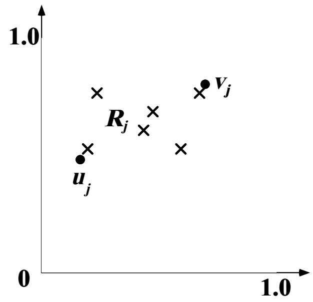


Fig. 7. Weight Representation of Fuzzy ART.

On-Line Visual Learning Based on Fuzzy ART Model First, we describe summary of fuzzy ART model (**Fig.**6) on the basis of literature [5]. Next, we present how to transform YUV space into $Yr\theta$ space.
Input vector: Each input $\boldsymbol{a}$ is an $M-$ dimensional vector, where each component a_i is in the interval $[0, 1]$.
Complement coding: An normalization rule called *complement coding* achieves normalization while preserving amplitude information of the input vector: $a_i^c \equiv 1 - a_i$. The complement coded input $\boldsymbol{a}$ to the fuzzy ART model is the $2M-$ dimensional vector: $\boldsymbol{I} = (\boldsymbol{a}, \boldsymbol{a}^c) \equiv (a_1, \cdots, a_M, a_1^c, \cdots, a_M^c)$.
Weight vector: Each category j corresponds to a vector $\boldsymbol{w}_j = (\boldsymbol{u}_j, \boldsymbol{v}_j^c)$, where $\boldsymbol{u}_j$ and $\boldsymbol{v}$ represents one corner of hyper-rectangle R_j, respectively. In case of $M = 2$, geometorical representation of a category j is shown in **Fig.**7.
Parameters: The fuzyy ART operation is determined by a choice parameter $\alpha > 0$, a learning rate parameter $\beta \in [0, 1]$ and a vigilance parameter $\rho \in [0, 1]$. A Fuzzy ART system includes a field F_0 where its nodes represents a current input vector, a field F_1 which receives both bottom-up input from F_0 and top-down input from a field F_2 that represents category.
Category choice ①**:** For each input $\boldsymbol{I}$ and category j, the choice function T_j is defined by

$$T_j(\boldsymbol{I}) = \frac{|\boldsymbol{I} \wedge \boldsymbol{w}_j|}{\alpha + |\boldsymbol{w}_j|}$$

where for any $M-$ dimensional vectors p and q, $\wedge$ denotes the 'min' version of the fuzzy AND operator defined by

$$(\boldsymbol{p} \wedge \boldsymbol{q})_i = \min(p_i, q_i)$$

and || denotes the norm defined by $|p| = \sum_{i=1}^{M} |p_i|$. When at most one F_2 node can become active at a given time, the system is said to make a *category choice.* The category choice is indexed by J, where $T_J = \max T_j : j = 1, \cdots, N$. If more than one T_j is maximal, the category j with the smallest index is chosen. In particular, nodes become committed in order $j = 1, 2, 3, \cdots$.

Resonance or reset ②: *Resonance* occurs if the match function of the chosen category meets the vigilance criterion; that is, if $|\boldsymbol{I} \wedge \boldsymbol{w}_J| \geq \rho|\boldsymbol{I}|$, learning takes place as defined below. *Mismatch reset* occurs if $|\boldsymbol{I} \wedge \boldsymbol{w}_J| < \rho|\boldsymbol{I}|$. In this situation, the match function T_J is set to 0 for the duration of the current input presentation to avoid the persistent selection of the same category during search. A new index J maximizing the choice function is chosen, and this search process continues until the chosen J leads to resonance.

Learning ③: Once search ends, *learning* takes place by updating the weight vector according to the following equation:

$$\boldsymbol{w}_J{}^{new} = \beta(\boldsymbol{I} \wedge \boldsymbol{w}_J{}^{old}) + (1 - \beta)\boldsymbol{w}_J{}^{old}$$

By definition, *fast learning* corresponds to setting $\beta = 1$

According to the original algorithm of fuzzy ART system, many categories which overlapped each other are generated. This situation is not suitable for image segmentation. So, we refine the original algorithm of fuzzy ART system so as to exclude extra categories each of which includes few sample data. We use a density D_i of sample data in each category i as a criterion for excluding extra categories. We define this density as follows:

$$D_i = \frac{\#\text{ of sample data included in category } i}{\text{Volume of category } i}$$

Based on this density D_i, we segment categories into two groups by using general clustering algorithm such as K-means algorithm [9]. Categories with high density D_i are selected as final results of our on-line visual learning algorithm.

Color Space Transformation for On-Line Visual Learning Color image we deal with is represented by YUV color space which is standard color space used for analogue television transmission. YUV color space is a mathematical representation of the human eye's response to color. Y is the luminance component, U and V are the chrominance components. Although YUV space well reflects the human eye's response to color, YUV space is not suitable for inputs of fuzzy ART model. In order to make it suitable for inputs of fuzzy ART model, YUV space is transformed to a particular color space called $Yr\theta$ color space which is linearly separable using only plance parallel to the principle axes. We define the transformation of YUV color space to $Yr\theta$ as follows:

$$y = y, \quad r = \sqrt{u^2 + v^2}, \quad \theta = arc\tan\frac{u}{v},$$

where r and θ indicate saturation and hue components, respectively. In UV space, the neighboring area with color similar to (u, v) forms arc region. On the contrary, this neighboring area, that is, a cluster with similar color forms rectangular region in $r\theta$ space. This transformation enables fuzzy ART model to segment color image in on-line, because a cluster with similar feature in fuzzy ART model is also represented by a hyperrectangle.

A Preliminary Result of Color Segmentation Based On Fuzzy ART Model **Fig. 8** shows an example of a real image captured by a color CCD camera. The size of a captured image is 300×200 pixels. In this figure, there are five wide stripes and four narrow stripes. Each color of these five stripes corresponds to light blue, red, yellow, green, and blue in this order. The color of all four narrow stripes is white. **Fig. 9** shows the projection of a source color image to $Yr\theta$ color space. As shown in this figure, the $Yr\theta$ color space can be segmented by the cuboids as shown in **Fig. 9**.

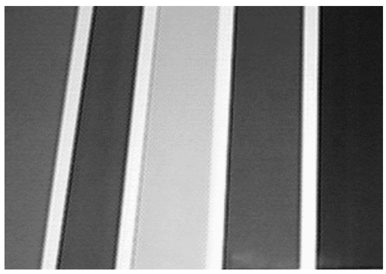


Fig. 8. A source color image.

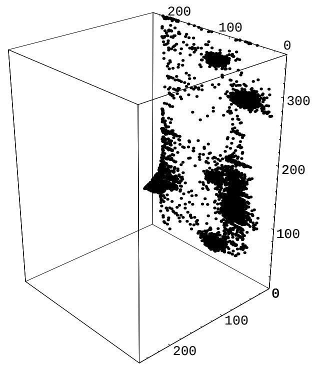
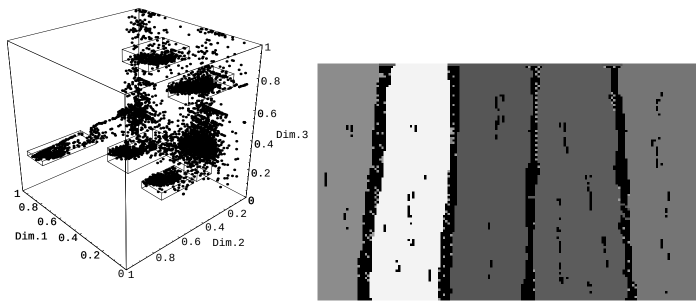


Fig. 9. $Yr\theta$ Color Space.

As shown in **Fig. 10**, our color segmentation algorithm succeeds in extracting a red, yellow, green, blue, light blue, and white regions, respectively. To make readers understand this result, **Fig. 10** (a) shows both of sample data and obtained categories. Each cuboid corresponds to a category produced by our modified fuzzy ART system. **Fig. 10** (b) shows a segmented image of a source color image.



(a) (b)

Fig. 10. A result of clustering the given color image based on Fuzzy ART model.

Simple Color-Based Tracking Our simple tracking method is based on tracking regions with similar color information from frame to frame. We define a fitness function $\Phi_{target}(x, y)$ at a pixel (x, y) as a criterion for extracting a target region in the image,

$$\Phi_{target}(x, y) = \begin{cases} 1 & \boldsymbol{C}(x, y) \in \boldsymbol{CM}_{target} \\ 0 & \text{Otherwise} \end{cases}$$

,where $\boldsymbol{C}(x, y)$ and $\boldsymbol{CM}_{target}$ show a $Yr\theta$ value at (x, y) and a color model for a target represented by a cuboid, respectively. Based on $\Phi_{target}(x, y)$, the best estimate $(\hat{x}_{target}, \hat{y}_{target})$ for the target's location is calculated as follows:

$$\hat{x}_{target} = \frac{\sum_{(x_i,y_i)\in R} x_i \Phi_{target}(x_i, y_i)}{\sum_{(x_i,y_i)\in R} \Phi_{target}(x_i, y_i)}, \quad \hat{y}_{target} = \frac{\sum_{(x_i,y_i)\in R} y_i \Phi_{target}(x_i, y_i)}{\sum_{(x_i,y_i)\in R} \Phi_{target}(x_i, y_i)},$$

where R shows the search area. Initially, R implies an entire image plane. After initial estimation for the location of the target, we can know the standard deviations $\sigma(\hat{x}_{target})$ and $\sigma(\hat{y}_{target})$ regarding $(\hat{x}_{target}, \hat{y}_{target})$. Therefore, based on the deviations, R is restricted to a local region during the tracking process as follows:

$$\begin{aligned} R : \{(x, y)| \\ &\hat{x}_{target} - 2.5\sigma(\hat{x}_{target}) \leq x \leq \hat{x}_{target} + 2.5\sigma(\hat{x}_{target}), \\ &\hat{y}_{target} - 2.5\sigma(\hat{y}_{target}) \leq y \leq \hat{y}_{target} + 2.5\sigma(\hat{y}_{target})\}. \end{aligned}$$

$\sum_{(x_i,y_i)\in R} \Phi_{target}(x_i, y_i)$ shows the area of the target in the image. Based on this value, we judge the appearance of the target. If this value is lower than the pre-defined threshold, the target is considered to be lost, then R is set to be the entire image plane for estimation at next time step. We set this threshold for the target area $= 0.05 * S$, where S shows the area of the entire image. This process helps to reduce the computational cost for extracting regions with similar color.

4.5 Behavior generator

The behavior generator decides the robot's behavior such as avoiding a wall (called avoiding behavior) or shooting a ball into a goal (called shooting behavior).

Avoiding behavior We implemented avoiding behavior so that the robot might avoid a wall using tactile sensors. We divided 32 tactile sensors into 4 groups ;
$a(1 \cdots 8)$: left front, $b(9 \cdots 16)$: right front,
$c(17 \cdots 24)$:left back, $d(25 \cdots 32)$:light back
Avoiding behavior is implemented as follows:

Read the state of tactile sensor
from the shared memory
switch(position)
  a: move backward and turn right
  b: move backward and turn left
  c: move forward and turn right
  d: move forward and turn left

This behavior has top priority over all other behaviors. As a result, whenever the robot collides with an object, it always avoids it.

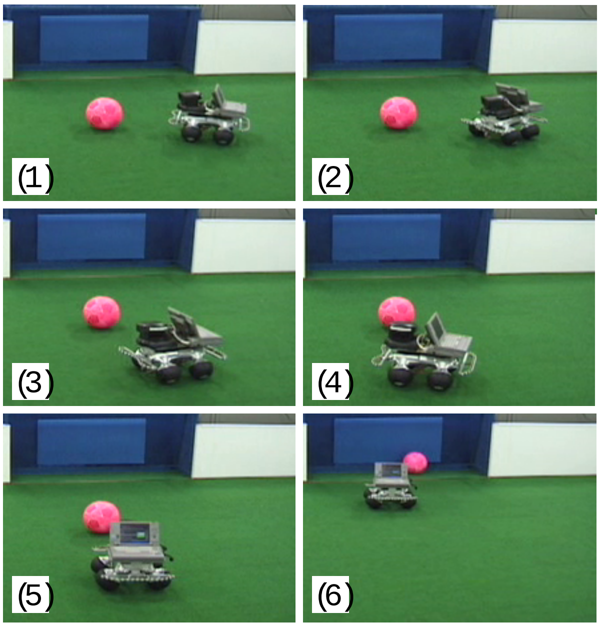


Fig. 11. Shooting behavior. (1):Approach the ball. (2),(3),(4):Round the ball. (5),(6):Kick the ball.

Shooting behavior We make a simple strategy for shooting the ball into the goal. To shoot the ball to the goal, it is important that the robot can see both ball and goal. Therefore, the robot must round the ball until the robot can see both ball and goal with the camera toward the ball. Finally, the robot kicks the ball strongly. **Fig.**11 shows the shooting behavior.

The concrete procedure of shooting behavior is follows:

1)Find the ball
2)Approach the ball
    While approaching the ball
    if the area of the ball $>$ 20 **then** stop
3)Round the ball
    d $\leftarrow$ the direction of the goal
    switch(d)
        right: clockwise round the ball
            with the camera toward the ball
        left: counterclockwise round the ball
            with the camera toward the ball
    if the robot can see both ball and goal **then** stop
4)Turn the body of the robot toward the ball
5)Kick the ball strongly

5 Discussion

In this paper, we described how to construct a cheap multisensor-based mobile robot system which consists of mainly made from state-of-the-art portable PC, a battery-powered R/C model car, a CCD camera and a set of tactile sensors by remodeling a keyboard. Since these components are commercially available, we can construct the total system at comparative low cost. Our robot system might be used as a personal robot which can be used at home since its price would be low and its performance would be high. Now, we use this multisensor-based mobile robot as a standard platform for robotics soccer research. In the future, we plan to realize

- robust behavior based on sensor fusion between visual and tactile information, and
- cooperative behavior with other robots.

In this paper, we also describe a method for on-line visual learning for color image segmentation on the basis of fuzzy ART model and color space transformation. Currently, we only implemented one-shot learning for color image segmentation. That is, an input color image is given to our learning algorithm. So, we have to improve our implementation so as to manage a seguence of images. But, we think it is easy to do this because fuzzy ART architecture has the mechanism which is suitable for on-line learning. We will finish realizing total system this until RoboCup-98 Workshop is held.

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