A neurally controlled robot competes and cooperates with humans in Segway soccer

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***Abstract*— A new RoboCup soccer league is being developed, focusing on human-robot interaction. In this league each team consists of both a human player, mounted on a Segway HT scooter, and a robotic version of the Segway; both human and robot players must cooperate to score goals. This paper details the design of our robotic Segway Soccer Brain-Based Device (SS-BBD). The SS-BBD control system is based on a large scale neural simulation, whose design is dictated by details from the published literature on vertebrate neuroanatomy, neurophysiology, and psychophysics. The physical device is completely autonomous, and possesses special manipulators for kicking and capturing a full-sized soccer ball. The SS-BBD uses visual and laser rangefinder information to recognize a variety of game related objects, which enables it to perform actions such as capturing the ball, kicking the ball to another player, shooting a goal, and maneuvering safely across the field. The SS-BBD can act autonomously or obey voice commands from the human player. This is an unprecedented level of human-robot teamwork on a soccer field, in that our players are not merely acting autonomously, but also communicate with each other and support each other on the field.**

I. Introduction

RoboCup [1] is an organization dedicated to fostering robotics research by providing a standard problem, robot soccer. The stated goal is to develop, by 2050, a team of fully autonomous humanoid robots that can win against the human world soccer champion team. However, all current RoboCup leagues involve only robots playing other robots. A new RoboCup league, Segway Soccer [2], [3], is under development in which humans and robots interact on the playing field. We hope that this new league will be as useful to the field of human-robot interaction as previous RoboCup leagues have been to the field of multi-agent coordination.

Our Segway soccer playing robot was constructed as a Brain-Based Device (BBD). A BBD is a class of neurally-controlled robot, which is based on features of vertebrate neuroanatomy and neurophysiology, emphasizing the organism's interaction with the environment [4]. A BBD is constrained by the following design principles:

1) The device needs to engage in a behavioral task.
2) The device's behavior is guided by a simulated nervous system having a design reflecting the brain's architecture and dynamics.
3) The device needs to be situated in the real world.

The behavior of a BBD arises from the interaction between the simulated nervous system, the device's phenotype, and the environment.

The Segway Soccer Brain-Based Device (SS-BBD) presented in this paper is a hybrid device, combining a neural simulation with more traditional control methodologies. It operates in a game with many rules and constraints, not the least of which is that it must interact with human players in a safe and effective manner. The SS-BBD is successful in the sense that it: 1) can visually recognize objects in a cluttered natural environment; 2) can perform difficult motor skills; 3) has novel and effective algorithms for action selectionl; and 4) has competed and been victorious in a series of games with another Segway Soccer team.

II. Segway Soccer Game

Segway Soccer is relatively new, and the rules [3] are still under development. The object of this league is to have both human players and robots cooperate and compete with each other, in a game on an equal footing.

Games may be two-a-side or more, up to 11 on a team, and half of the team members must be robots[1]. For safety reasons, players are not allowed to get closer than one meter to each other, and the robots must therefore have an advanced obstacle avoidance and route selection mechanism or they will frequently be stuck in the corner of the field, prevented from moving by other players.

As in other RoboCup leagues [1], color markers are used to help the robots' object recognition ability: the ball is orange, the goals have separate colors and each team has its own color which has to be announced to the opponent team 20 minutes before the game.

To ensure the cooperation between human and robot players and to avoid the dominance of humans:

- Dribbling and traveling is not allowed. The player (either human or robot) who has the possession of the ball may turn in place, but must not move off the spot. The player has 30 seconds to pass the ball onwards or possession turns over to the other team.

[1]The team presented in this paper consists of one human, one robot.

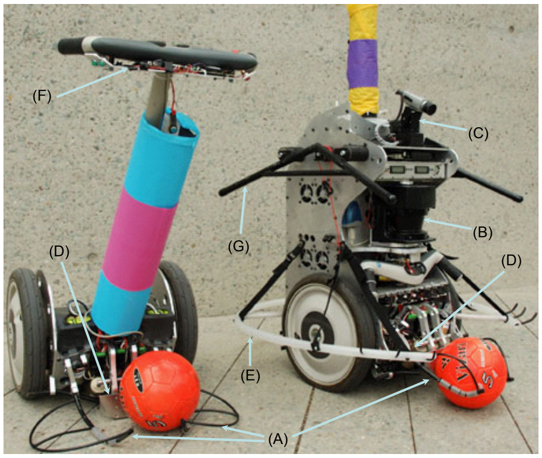


Fig. 1. The Segway Soccer devices. On left the modified Segway HT scooter for the human player, which gives the rider the same active ball-handling and kicking capabilities as the SS-BBD on the right. (A) active capture devices, (B) laser rangefinder, (C) pan-tilt unit and camera, (D) kicking assembly, (E) passive capture ring, (F) voice command module, (G) crash bars.

- No shot on the goal is allowed unless both human and robot players have touched it since that team last took possession of the ball. Moreover, to further increase the robots' dominance on the field, at the recent 2005 US Open [1] only robots were allowed to shoot on goal.
- Human players are not allowed to mark (i.e., closely shadow) robots.

As a consequence of these rules Segway Soccer is a more cooperative game with fewer scrum-like plays than other RoboCup leagues. A typical offensive play consists of a series of passes between teammates in which player[s] without the ball head towards the goal. When a player close to the goal receives a pass it shoots on the goal. The defensive team concentrates on intercepting the opponent's pass, capturing a free ball, and on defending territory. By occupying territory, that area and passage through it are denied to the other side, due to the one meter rule. This is typically most useful in preventing the opponents from getting close enough to the goal to score.

III. The Devices

The SS-BBD (see Fig. 1) is based on the Segway Robotic Mobility Platform [5], a commercially available robot version of the Segway Human Transporter (HT). An aluminum chassis sits on the commercial base, containing a cluster of six compact Pentium IV PCs and enough battery capacity to power it for 45 minutes.

The SS-BBD possesses various sensory systems, including a color camera, a laser rangefinder, and a digital compass. Banks of short range IR proximity sensors are mounted low around the device to detect nearby soccer balls. One bank of IR sensors is mounted on the back above ball height to detect nearby non-ball obstacles that are outside the sensing arc of the front-mounted camera and laser rangefinder.

The SS-BBD possesses solenoid actuated devices that enable it to handle a soccer ball. A pair of flexible jaw-like plastic catchers can pinch a ball firmly against the front of the device, allowing it to rotate in place with a ball. To kick the ball, the catchers are raised and a second set of solenoids actuates a kicker plate that delivers thrust to the ball. A passive device, a ring of flexible plastic suspended from straps, aids in capturing incoming balls on the sides and back. Balls slip under the ring and are trapped against the SS-BBD. The low-mounted IR sensors then detect on which side of the device the ball is located, and a simple pivot-in-place motion allows the device to turn until the ball is on its front face, at which point it captures the ball with the solenoid-driven catchers.

A modified Segway HT scooter for the human teammate has the same solenoid driven catchers and kicker as the SS-BBD, and has a similar maximum velocity to the SS-BBD. Thus both human and robot have roughly comparable physical capabilities in ball-handling, which helps to prevent the human player from completely dominating the game.

For more detailed information on the physical design and function of these devices, please see our ICRA 2006 poster submission [6] and on-line videos [7].

IV. Simulated Nervous System

The physical device is guided by a hybrid control system (see Figure 2) consisting of a simulated nervous system and more traditional mathematical and control algorithms. The simulated nervous system is based on a simplified model of vertebrate nervous system. The neural simulation is primarily responsible for object recognition and sensorimotor control; the non-neural controllers provide higher level action selection.

A neuronal unit in the SS-BBD is simulated by a mean firing rate model, where the mean firing rate variable of each unit corresponds to the average activity of a group of $\sim$100 real neurons during a time period of $\sim$30 ms.

Figure 2 describes the overall architecture of the control system, which can be described as follows. IR sensors, a firewire camera and a laser rangefinder provide sensory input for the system. Action Selection is the central module; it receives input from IR sensors and the neural visual system (See Figure 3). Action Selection sends direct commands to some actuators and indirect ones to the SS-BBD's wheel through Head and Body movement neuronal areas. The device's movement may also be affected by an obstacle detection and avoidance mechanism.

V. Vision

To ensure effective behavior, robot soccer requires fast, robust visual information processing to identify objects on the playing field.

The visual information was provided to the SS-BBD by a Sony IEEE 1394 camera equipped with a wide angle lens working at 30 frames per second and 640×480 pixels. The raw sensory pixel data was immediately separated into luminance and color channels (YUV colorspace). Visual information is processed by the neural simulation (see figure 3); the luminance information feeds into a set of edge detecting neuronal areas and the color information drives neuronal areas dedicated

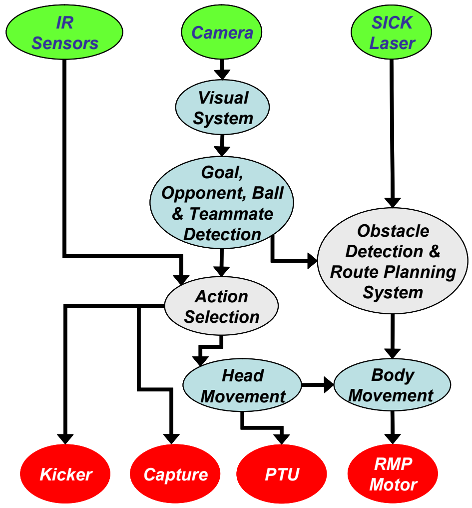


Fig. 2. Control architecture of the SS-BBD. Green: sensors; Cyan: neuronal areas; Gray: non-neural controller components; Red: actuators. The simulation has 60000 neuronal units and 1.6 million synapses. See Section IV for details.

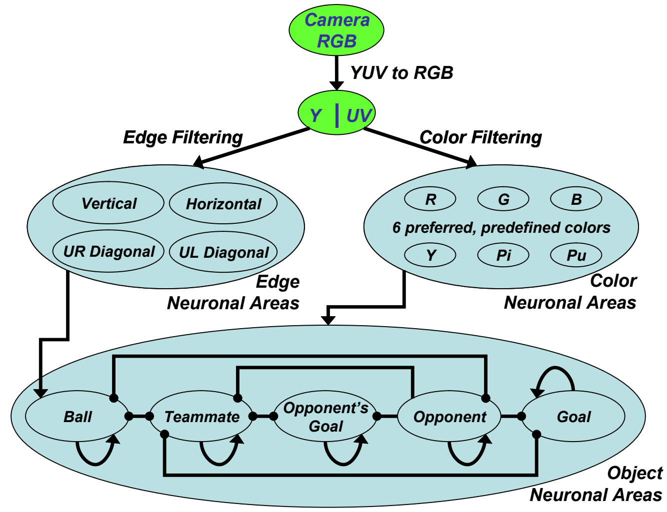


Fig. 3. Schematic neural architecture for the visual system and object detection. RGB images are converted to YUV. The Y (luminance) channel is Gabor filtered , and the UV domain is color filtered to produce activity in neuronal areas tuned to specific edges and colors. Each object detection neuronal area takes a specific conjunction of particular color and edge areas as its input. Cross-inhibition and self-excitation of object areas improves recognition. All the connections in the processing stream are retinotopic. Arrowed line: excitatory connection; Circle-tipped line: inhibitory connection. Green: sensory inputs; Cyan: neuronal areas.

to detecting particular game-related colors. Information from these early visual areas is combined in neuronal areas that detect game-related objects.

A. Preferred colors

There are five important objects on the field with different colors or color combinations: our goal, opponent's goal, ball, teammate and opponent. The visual system uses six neuronal color groups, each of them having a preferred color, namely Red, Green, Blue, Yellow, Pink and Purple (See Figure 3). To speed up the mainly color-based object recognition, we designed a tool to easily recognize these preferred colors by creating a lookup table for each color on the UV color space. A value in a color table can be regarded as the probability of a particular UV coordinate belonging to that specific color. Snapshots from the user interface to create a color lookup table is presented in Figure 4.

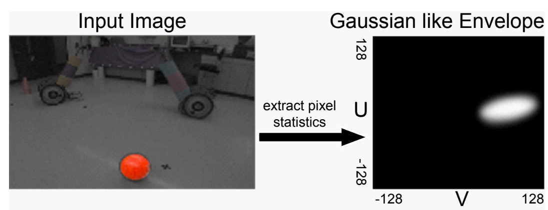


Fig. 4. Creating a preferred color lookup table in the UV domain. The user crops an area of the visual field that consists of only the selected color (e.g., a red ball). Based on the UV values of the pixels in the cropped area, a statistical algorithm generates a Gaussian-like two-dimensional probability surface on the UV space. This surface is saved and used as a lookup table to generate neuronal activity given a pixel's UV value.

B. Neuronal Visual Areas and Object Recognition

The visual and object recognition nervous system contained 15 neuronal areas. Figure 3 shows a high level diagram of the system including the various neuronal areas and the arrangement of the feedforward and recurrent excitatory and inhibitory synaptic connections. The simulation is based on a recent model of the primate visual system [8], where the edge and color filtering neuronal areas correspond roughly to primary and secondary visual cortices and the object recognition neuronal areas perform similar functions to inferotemporal and parietal cortices.

The color and edge groups of the neuronal visual areas are retinotopically mapped. The activity of each color neuronal unit is determined by the relevant color lookup table; this activity denotes the 'closeness' of it's pixel in the image to the preferred color of the group. Similarly, the activity of a unit in an edge group is proportional the output of the relevant edge filter at that pixel.

In the SS-BBD's neural model, each object the robot had to recognize on the playing field had its own neuronal area, namely Ball, Goal, Teammate, Opponent, Opponent's Goal areas (See Figure 3). These object groups received their topographical inputs from one or more color neuronal groups. Some objects are detected through single colors: for example, the ball is orange, our goal is purple, and the opponent's goal is pink. Teams, however, are denoted by combinations of colors: our team is purple and yellow on the same color marker. For these objects, the corresponding neuronal area recognizes conjunctions of these colors in the nearby topographic locations. The ball neuronal area is unique in that the ball can also be recognized by its shape: a conjunction of edges in a particular configuration.

The object areas had recurrent self-excitatory connections and some also had inhibitory connections to the other object areas. Inhibitory connections made the system more robust:

Objects that should not be in the same place in the visual field have inhibitory connections between their neuronal groups.

In summary, the visual object recognition was based on color/shape information, tuned self-excitation, and cross inhibition between the object groups. All these together made it possible for the neural simulation to robustly recognize objects in real-time under a variety of lighting conditions.

VI. Head-Body Object Tracking: Connection of Visual and Motor Neuronal Areas

The target tracking behavior of the SS-BBD is analogous to humans' [9], [10]: a fast camera saccade foveates the target object and then the slower body turns to follow while the camera tracks the object smoothly.

Both the apparent retinal position and velocity of the target object are used to generate camera pan-tilt position commands, which in turn generate wheel velocity commands. Anticipated retinal position (function of the target object's position and velocity) generates retinotopic activity in neuronal areas projecting to motor areas driving the pan-tilt unit. For example, if the object is right of center moving rightwards, then there is more activity on the right side of the pan motor area, which drives the pan unit rightwards. Similarly, up-down displacement of neuronal activity drives the tilt motor.

The current pan-tilt position is transformed into neural activity that is topographic, with respect to body centered coordinates, and is projected to body movement areas. For example, when the camera is pointed to the right, there is more activity on the right side of the body rotation area, which causes the body to turn rightwards. Similarly, the tilt position controls forward speed: a higher head position means the object is far and speed is high, a lower head position means the object is close and speed is slow.

The total system produces a cascade of neuronal activity that comes from visual areas to the motor areas, which in turn creates a change in behavior and visual input. The design of this architecture ensures that the camera will tend to lead a moving object rather than lag it, and the body motion will follow the head with a smooth trajectory. The different maximum speeds of camera and body motion prevent tracking behavior from oscillating.

VII. Action Selection and Motor Commands

The non-neural elements of the controller are organized on two levels: behaviors and plays.

Behaviors are atomic actions that the device undertakes, such as searching for an object, or kicking the ball. Each behavior is a separate controller that sends commands to the motor neuronal areas independently of the other behaviors. Only one behavior can be active at any one time. A behavior may take input directly from the sensors or input pre-processed from the sensory neuronal areas. A play is composed of a sequence of behaviors, and the sensory conditions that will cause the controller to transition to each new behavior. All plays draw on the same set of possible behaviors, but recombine them in various way to produce different results.

Finally, a mechanism exists that allows the human player to override the normal autonomous execution of plays by the SS-BBD. A voice command system is installed on the human player's Segway Scooter that wirelessly relays a command to the SS-BBD causing it to execute a new play requested by the human player.

A. Behaviors

The behaviors used by the SS-BBD are:

Find Object: Pan the camera and turn the SS-BBD in place, until a target object is visually recognized.

Track Object: Approach a target object while keeping it foveated using both the pan-tilt unit and the wheels of the SS-BBD.

Capture Ball: Perform the final manuevering to get close to the ball and lowers the catchers to trap it.

Kick: Lift the catchers away from the ball and fire the kicking solenoids.

The Kick and Capture Ball behaviors are simple, precisely tuned controllers. Capture Ball is a proportional controller that uses feedback from both the neuronal visual ball area and non-neural signals direct from the IR to guide the SS-BBD to the correct point to capture the ball, at which point is actuates the solenoids. Kick is an open-loop sequence of commands to catcher solenoids, kicker solenoids, and the wheels that results in a straight, powerful kick travelling about 1.5 m/s. Both behaviors have some error correction logic that can correct or re-start the process if the ball is not successfully kicked or captured.

The behaviors Find Object and Track Object can be set to work on any object that is detected by the neural simulation: soccer balls, either goal on the field, a teammate, or an opponent. Find Object has two different algorithms depending on the circumstances of its execution: (1) if called during a momentary loss of an object that had been previously tracked, Find Object steers the search in the same direction in which the object was last observed to travel, thus following the path of an object that has been momentarily occluded by some obstacle; (2) if called for a brand new search, Find Object searches in a random direction for the target object. Since the pan-tilt unit tracks faster than the device's body can turn, it first performs a head-check for the object to the limits of the pan in one direction. If the object is not found, the camera goes to the pan-limit on the other side and the body turns to follow the head.

The Track Object behavior is based on psychophysical data about eye-head-body coordination, and is implemented using neural mechanisms, as discussed in section VI. Track Object will cause the SS-BBD to move forward while turning towards the target when it is not in possession of the ball (e.g., while chasing a loose ball). If it is in possession of the ball (e.g., when lining up a shot on the goal) then it rotates in place without forward motion.

When moving forward, Track Object uses an obstacle avoidance and route selection algorithm, based on human behavior, that balances target-seeking with obstacle-avoiding.

(a) Too close! Backup. . .
(b) find the goal and track towards it. . .
(c) avoid smoothly around the moving opponents. . .
(d) and wait for the pass in front of the goal.

Fig. 5. An example sequence of SS-BBD avoidance during the Run Downfield play in a cluttered, dynamic environment. The SS-BBD and its teammate wear yellow-purple-yellow markers, and the opponents wear fluorescent green. The motion of the SS-BBD in the near future is indicated by the yellow arrow. The yellow circle indicates the SS-BBD is stationary.

Human locomotion to a goal in the presence of obstacles can be described and predicted by a simple dynamical model [11]. The model is a spring-mass-damper type equation controlling the angular velocity of the agent given the distances and headings to the target object and the obstacles. Track Object implements the same dynamical model. Obstacle information comes from a laser rangefinder; an obstacle is defined as any set of adjacent laser readings subtending at least 3° of arc that are all less than two meters from the rangefinder. Target information is extracted from the neuronal activity of the target object area and the pan position areas; the center of activity in the object area produces a vision-centered coordinate which is added to the center of activity of the pan position area to produce a body-centered coordinate.

Since this device operates in a real environment with stringent safety requirements, the velocity of the SS-BBD is subject to additional constraints. The normal maximum forward speed of the device is $3.5\ m/s$, but this is reduced proportional to the average distance of all obstacles detected by the laser rangefinder. This increases safety by reducing speed in cluttered environments. Additional safety is provided by backing up slowly if an obstacle is less than $1\ m$ away in the front arc, as long as there are no obstacles within $1\ m$ in the back arc (as determined by rear IR sensors).

Examples of typical avoidance paths using these algorithms can be seen in figure 5 and in on-line videos [7].

B. Plays

Plays are a higher level of control than behaviors. A play is a state machine where the state is either a particular behavior or another play. The set of conditional transitions between the states determine the flow of control that defines the play.

Most of the plays used on the SS-BBD are at the level of very simple actions on the field, such as ‘chase the ball’, or ‘pass to the teammate’, or ‘run downfield until near the goal’. Figure 6 shows state automata that represent the basic plays Chase, Pass, and Run Downfield. Other basic plays in the repertoire are Shoot (which is identical to pass, except the target object is the opponent’s goal), Run Upfield (identical to Run Downfield, except for the target), Follow the Teammate, Mark the Opponent, Block our Goal, and Wait (stay in place, tracking the ball, but not moving forward until the ball is near enough to capture).

The SS-BBD also possesses a number of plays that are more complicated, composed of the basic plays. One such offensive maneuver is designed to move the ball down the field. The flow of the play goes from Chase to Pass to Run Downfield. When Run Downfield is complete it returns to Chase and the sequence repeats. Each sub-play in the sequence transitions to the next sub-play when it has finished its normal execution.

C. Voice Commands

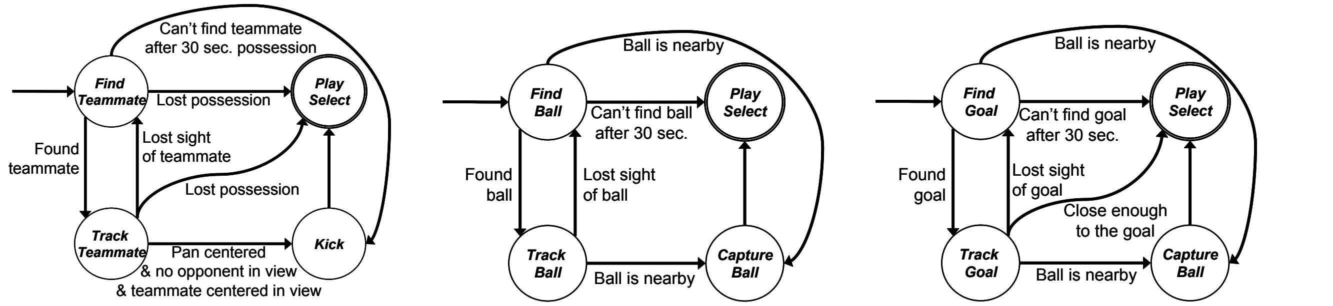
At any point the flow of control can be interrupted by a voice command from the human teammate. The Segway HT scooter ridden by the human has a voice recognition board (Voice Extreme^{tm} Toolkit, Sensory, Inc., Santa Clarita, CA) connected to a microphone that can recognize about a dozen discrete short phrases after being trained to a particular voice. These phrases are code names for various plays in the SS-BBD’s repertoire, and for each such phrase a corresponding command is transmitted wirelessly to the SS-BBD, which upon receiving the command immediately executes the correct play.

VIII. Segway Soccer Exhibition

At the 2005 RoboCup American Open in Atlanta, Georgia, a set of Segway Soccer demonstration games were held to promote this new RoboCup league. The demonstration was a great success; both The Neurosciences Institute and Carnegie Mellon University fielded [12] two-a-side teams. Several more institutions are presently in the process of developing their own teams. Both of the teams on the field in Atlanta were able to demonstrate safe human-robot interaction in a competitive situation. Both teams showed that they could take control of the ball, move it around the field through human-robot cooperation, and score. However, we should like to modestly point out that we won all five demonstration games.

IX. Conclusion

The SS-BBD is unique among neurally-controlled soccer robots in both the biological detail underlying its design and in the complexity of the neural simulation. It is unique among BBDs in the complexity of its behavioral repertoire and in the speed of its action.



(a) Pass to Teammate (b) Chase the Ball (c) Run Downfield

Fig. 6. State machines showing how three basic plays are composed of behaviors and conditional transitions between them. When Play Select is reached another play is chosen and executed.

Although mimicking biology has in recent years become a well-accepted approach to building robotic systems (see, e.g. [13], [14]), we are particularly interested in behavioral control at the level of systems neuroscience. Large-scale neural simulations of vertebrate neuroanatomy and neurophysiology are used to test hypotheses of how real nervous systems function (e.g. [4], [15]–[20]). We feel it is important that such neural simulations are embodied in a real-world device interacting with a rich environment, rather than operating in abstract simulation worlds. Much of the complexity of animal behavior results from the interactions between the nervous system, the rest of the body, and the environment. And although our primary focus is on biological modelling, we also feel that the Brain-Based Device approach offers insights for designing robots that need to survive and accomplish tasks in dynamic environments with robustness and adaptability that is difficult to obtain using traditional engineering and artificial intelligence methods. We applied the BBD method to the design of this Segway Soccer robot, and produced a device that is capable of interacting with humans both cooperatively and competitively, but most importantly, safely.

ACKNOWLEDGMENT

This work was supported by the Neurosciences Research Foundation, W. M. Keck Foundation, and the Defense Advance Research Projects Agency (DARPA).

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