Development of Multimodal Strategy Board for Improving Competitiveness in Goalball

Tomozumi Ikeda, Toshitake Araie, Akira Kakimoto, Keiichi Ninomiya, and Kazuhisa Ikeda

Abstract—**With the approach of the 2020 Tokyo Olympics and Paralympics, interest in sports for participants with disabilities has been steadily increasing. For Japan to be successful in the Paralympic sports, scientific and engineering support similar to that provided to other Olympic competitors is necessary. This study develops a multimodal strategy board to improve Japan's competitiveness in goalball, a team sport for visually impaired players. The proposed tool is composed of an image processing system that determines the ball's position and movement, and a strategy board that provides tactical information. This paper describes the method used to determine ball position from game video and the structure of a haptic device incorporated into the strategy board.**

Index Terms—**Disability sports, goalball, image processing system, haptic device, multimodal strategy board.**

I. Introduction

Tokyo has been selected to host the 2020 Summer Olympics and Paralympics. Since the announcement, interest in disability sports in Japan has increased significantly.

In recent years, it has become common to use information communication technology and image processing technology in sports science. With improvements in tracking methods for balls and athletes, the tracking accuracy of sports video has steadily improved [1], [2]. In team sports, the acquisition of extensive data on player movements and tactics is now possible. Research on systems to visualize team performance for strategy analysis has become mainstream, especially in ball sports such as American football, soccer, and volleyball [3]-[7]. In these systems, the positions of the players and the ball are recorded using a set of cameras. Players and coaches are then able to analyze the visual information using computers and scientifically evaluate the performance of both individual players and the team as a whole. In order to develop competitive sports for participants with disabilities in Japan, establishing a system that provides this type of scientific and engineering support is essential. In this study, we develop such a system for goalball, one of the Paralympics sports.

Goalball is played by two teams of three players each on a volleyball-sized indoor court (18 m long × 9 m wide) with a goal (9 m wide × 1.3 m high) at either end. The court is divided into six areas, three on each side of the court. Tactile markers set 3 m apart and extending the full width of the court define each team's orientation area, landing area, and neutral area. The game is played in two 12-minute halves. The aim of the game is to earn points by rolling or bouncing a ball (20 cm diameter, 1.25 kg) embedded with bells into the opponents' goal. The players are blind or visually impaired and wear eyeshades at all times. Teams alternate between offense and defense. Players on offense roll or bounce the ball from their end of the playing area to the other. The defensive players listen to the steps of the offensive player, the sound of the bells in the rolling ball, etc., to judge the position and movement of the ball, and defend their goal when the ball is pitched towards it.

Scientific analysis via image processing has previously been used in blind football (soccer) played by visually impaired participants [8]. In goalball, the Swedish and German teams have developed an efficient strategic support system for their players and teams. In contrast, in goalball in Japan, the coach typically takes notes while watching video after a game and "manually" assesses player positioning and team strategies. This makes it virtually impossible for the coach to provide timely technical and tactical coaching to his players during or immediately following a game.

Individuals with visual impairments are often referred to as being "information handicapped." They have difficulty recognizing pictures or characters, which means that tactical instructions given by coaches to visually impaired players are given orally since strategy boards or tablets that present graphic information cannot be used. As a result, players often have difficulty intuitively understanding the coach's strategies. Given this situation, it seems highly desirable to find ways to automate strategy analysis by using computers for data processing and to develop a sensory substitution system that transforms analytical data into audio/tactile information. Multimodal interface that interacts with a system through multiple communication modes—including visual and auditory modes—is already being used for information presentation in welfare engineering and virtual reality [9],[10]. A similar approach can be applied to sports.

The purpose of this study is to develop a multimodal strategy board for enhancing a goalball player's understanding of game tactics and for sharing tactical information within the team. This paper provides an outline of such a board and describes the method of ball position extraction from video used to generate data and the haptic device that is incorporated into the board.

II. Multimodal Strategy Board

Fig. 1 shows the multimodal strategy board system. The system includes an image/sound processing system, a computer for data analysis, a strategy board that provides

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information to the players, and a tablet on which coaches can formulate a tactical plan. Player positions and ball trajectories are detected by the image processing system, which consists of cameras and microphones. Data on the frequency and/or duration of time that the players and the ball spend occupying or traversing the various areas of the court are displayed in both a color-coded map and as numeric data. These data, along with a proposed tactical plan, are transformed into audio/tactile information and presented on the strategy board.

The multimodal strategy board system has two primary advantages:

- The visualized information can be used to analyze the contents of the game and allows a rethinking of the team's strategy in preparation for the next game.
- The multiple-sense-organ presentation promotes a better understanding of tactics by the players.

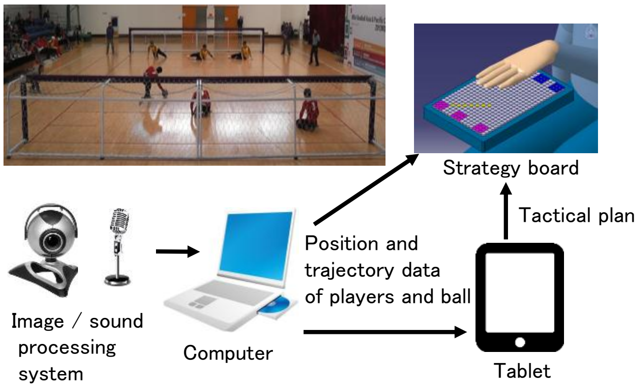


Fig. 1. Multimodal strategy board.

III. Ball Position Extraction

A. *Process of Ball Extraction*

In general, researchers in sports analysis use multiple cameras to acquire accurate, error-free data. At actual sporting events, a monocular camera is often used to acquire the appropriate video data. In this study, we used video data recorded by a monocular camera to extract the position of the ball. The analysis target is the video of a match filmed with a single home video camera. Ball position extraction is executed according to the flow shown in Fig. 2.

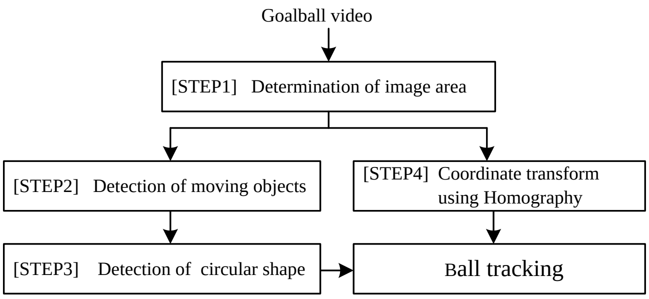


Fig. 2. Flow of ball position extraction.

[STEP1] *Determination of image area*.

A frame with no players or ball on the court is extracted as a calibration image. The surrounding area (windows, audience, etc.) is eliminated and the area to be analyzed is determined. This area is then applied to all images.

[STEP2] *Detection of moving objects*.

Moving objects are detected using the temporal difference method in which moving objects are identified by measuring the difference between I_t, the image at time t, and $I_{t-\Delta t}$, the image at time $t-\Delta t$. (In this step, the images are converted to grayscale.)

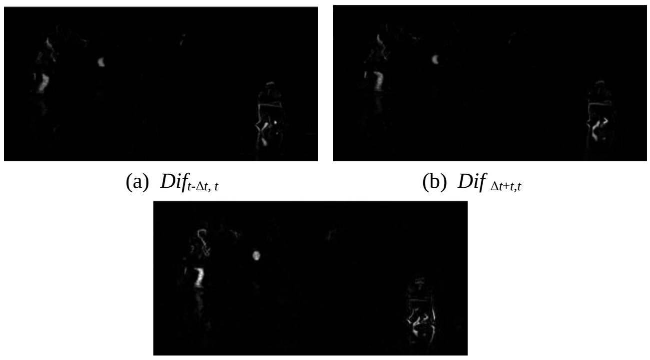
The temporal differences are thus calculated as

$$Dif_{t-\Delta t,t} = I_t - I_{t-\Delta t} \tag{1}$$

The logical product of two difference images $Dif_{t-\Delta t}$ and $Dif_{t,t+\Delta t}$ creates logical product image I_a:

$$I_a = Dif_{t-\Delta t,t} \cdot Dif_{t,t+\Delta t} \tag{2}$$

Fig. 3 shows an example of the detection of moving objects. As can be seen in panel (c), the ball is displayed as a bright circle against a black background. This is the result of a simple test: If the density value of difference image is greater than or equal to a designated threshold value, then the color of the target pixel is set to white; otherwise, it is black. (Black indicates that the two difference images are equal, i.e., there is no movement.) It is obvious here that only the players and the ball have been extracted.



(a) $Dif_{t-\Delta t,\,t}$ (b) $Dif_{\Delta t+t,t}$

(c) I_a

Fig. 3. An example of the detection of moving objects.

[STEP3] *Detection of circular shape*.

Because the ball in goalball is harder than a soccer ball and is difficult to deform, the shape of the ball in the image is nearly a perfect circle. In this study, we extract a candidate ball area using the circular Hough transform. First, the radius (pixel value) and the mean hue of the ball on the far side and the near side of the court are acquired, and the range of the radius is defined. The sensitivity coefficient of the circular Hough transform is also set. If the coefficient is set to a large value (close to 1), then more circular objects will be detected. In this example case, the radius range is set to [10, 30], the hue range is set to [0.2, 0.8], and the sensitivity coefficient is set to 0.90.

Next, the Hough transform is performed on the difference image obtained in STEP 2. As a result, all bright circles in the image within the radius range are searched for and the relative strength value of the center of the circles is obtained. The circles with the highest strength values determine the candidate ball areas (Fig. 4(a)). The hue in a candidate area is then compared with the hue of the ball, and the candidate area with the smallest difference is established as the area of the ball (Fig. 4(b)).

(a) Ball candidate area (b) Extracted Ball area

Fig. 4. An example of the detection of a circular shape.

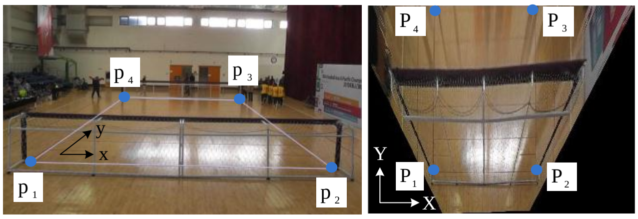
[STEP4] *Estimation of ball trajectory*

Acquisition of the ball trajectory on the court is obtained by projecting the ball trajectory obtained from the input image onto the overhead image using the homography transformation method. The homography matrix is calculated from the angle obtained from the court of the input image line and the point of the input image $p_1(x_1, y_1)$ to $p_4(x_4, y_4)$ and the point of the overhead image $P_1(X_1, Y_1)$ to $P_4(X_4, Y_4)$. (These points are the corners of the court.)

From the ball coordinates (x, y) on the input image and the homography matrix, the ball coordinates (x', y') on the overhead image are obtained according to equation (3). Here, the x-axis is the direction of the short side of the court, and the y-axis is the direction of the long side of the court:

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} \sim \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}. \qquad (3)$$

Fig. 5 shows an example of homography transform.



(a) Input image (b) Overhead image

Fig. 5. An example of homography transform

B. Evaluation Experiment

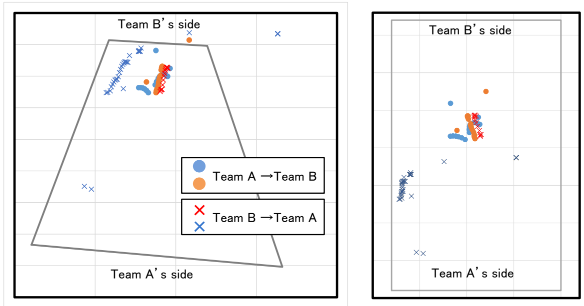
In the evaluation experiment, we used video data taken from the short side of the court. The resolution of the image was 1920 × 1080, and the frame rate was 30 fps.

The evaluation was done by finding the extraction rate and the accuracy rate from the number of frames with ball candidate areas N_c, and the number of error frames N_e (i.e., the number of frames where the extracted ball area is incorrect). Here, the accuracy ratio indicates the proportion of successes in extracting the ball candidate region. The accuracy rate is obtained from the following equation:

$$Accuracy\ rate(\%) = \left(1 - \frac{N_e}{N_c}\right) \times 100 \qquad (4)$$

Fig. 6 shows the estimated ball trajectory in (a) the input image and (b) the overhead image. Since the analyzed data were from video images taken from the short side of the court, the estimated range was about 7 m (Team B's landing area and neutral area), and accuracy with respect to depth was low.

Table I shows an example of accuracy ratio results when Team A is attacking Team B and when Team A is being attacked by team B. As shown in the table, the average accuracy rate was 91.8%. When there was a candidate area for the ball, it was possible to extract the ball with a very high probability. On the other hand, the average extraction rate was only 64.6%. In many cases where candidate areas were determined not to exist, the player and the ball, or the ball and the goal post overlapped, as shown in Fig. 7(b).

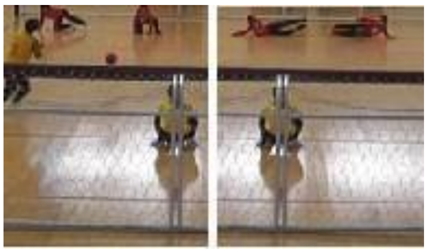


(a) Input image (b) Overhead image

Fig. 6. Estimated ball trajectory.

TABLE I: AS EXAMPLE OF ACCURACY RATIO RESULTS

	Team A →Team B		Team B →Team A		Average
Total number of frames	38	61	50	97	61
Number of frames with ball candidate area: N_c	17	18	14	36	22
Number of Error flames: N_e	1	2	0	6	2
Accuracy rate (%)	94.1	88.9	100	84.2	91.8
Extraction rate (%)	55.3	70.5	72.0	60.8	64.6



(a) success (b) error

Fig. 7. An example of ball extraction results.

As shown in Fig. 8, the estimable range was divided into 6 areas, and throwing patterns of the ball was analyzed. Table II shows the analysis results. It was found that Team A threw many balls from area 2 to area 5, and team B threw many balls from the right side of team B. It was suggested that this method was useful for acquiring data necessary for tactical analysis.

In the future, improving the accuracy of ball extraction and tracking using machine learning methods and particle filters will be a priority.

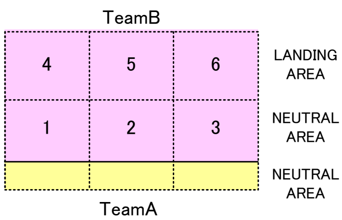


Fig. 8. Region for analysis of throwing patterns.

TABLE II: RESULT OF THROWING PATTERNS (OFFENSE AND DEFENSE TEN TIMES)

Team A →Team B			Team B →Team A		
Area	Area	Count	Area	Area	Count
1	4	0	4	1	3
	5	1		2	3
	6	0		3	0
2	4	0	5	1	0
	5	7		2	1
	6	0		3	0
3	4	0	6	1	0
	5	1		2	0
	6	1		3	3

IV. HAPTIC DEVICE FOR THE STRATEGY BOARD

Tactile displays and braille printers transform graphic information into tactile patterns that can be effectively displayed. These devices offer promising means for communicating with sports participants who are visually impaired.

In this study, we incorporated a prototype haptic device using a piezo actuator into our strategy board system. Fig. 9 shows the haptic device diagram. The device consists of a piezo haptic actuator (PiezoHapt actuator PHUA8060: TDK), a piezo haptic driver module (PWM Amp Module IFJ-001: Maruetsu), and a microcomputer (mbed NXP LPC1768: ARM). A signal formed with frequency and duty ratio related to the ball's arrival frequency and time is transmitted from a personal computer to the microcomputer. A PWM signal is generated by the microcomputer and the haptic actuator is driven by the amplified signal. When the analog switch is switched on, the haptic actuator works as a vibration sensor. The vibration signal is communicated to the microprocessors.

The PiezoHapt™ Actuator has a unimorph structure in which ceramic piezoelectric elements with electrodes on both sides are laminated on one side of a metal plate. The actuator can output various vibration patterns while driving at low voltage. Fig. 10 and Table III show the appearance and specifications of the piezo actuator. The unit is 80 mm long, 60 mm wide, and 0.4 mm thick.

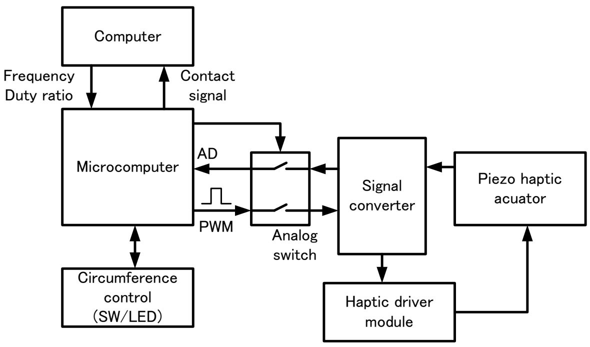


Fig. 9. Haptic device diagram.

The piezo haptic driver module was equipped with a PWM amplifier circuit and a step-up power supply circuit, and drove the piezo actuator efficiently and linearly. Fig. 11 shows the displacement of the haptic actuator during pulse driving in no load status (the input signal to the piezo haptic driver module has an amplitude of 5 V and a frequency of 1 Hz). The displacement of the actuator used here was approximately 62 μm; it instantly reacted to changes in input voltage. This result is similar to TDK's published information (https://product.tdk.com/). The actuator is capable of generating vibration in various patterns and displacements with waveform control.

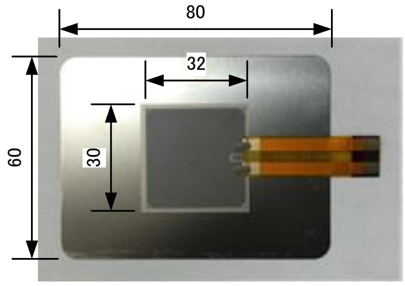


Fig. 10. TDK's PiezoHapt actuator.

TABLE III: SPECIFICATION OF PIEZO HAPTIC ACTUATOR

Vibration plate specifications	42Ni-Fe	
Electrode specifications	Width	12 mm
	Number of cores	2
	Insulation length	30 mm
	Lead pitch	7.0 mm
	Stripping length	5.0 mm
	Reinforcement	8.0 mm
Operation voltage	$24V_{P-P}$(±12V) max.	

A piezoelectric element generates voltage in response to mechanical pressure. When mechanical pressure (tapping, pressing) is applied to the actuator, an electric signal is generated, as shown in the Fig. 12. This function can be effective in communicating analytical information to players and coaches.

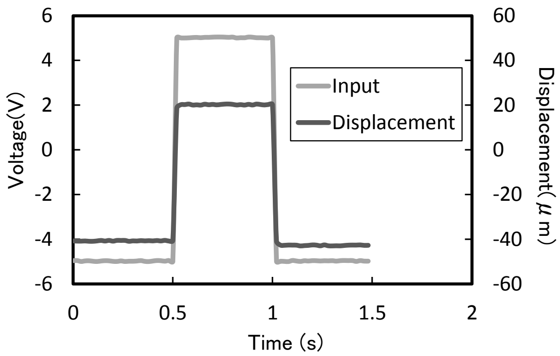


Fig. 11. Displacement of haptic actuator.

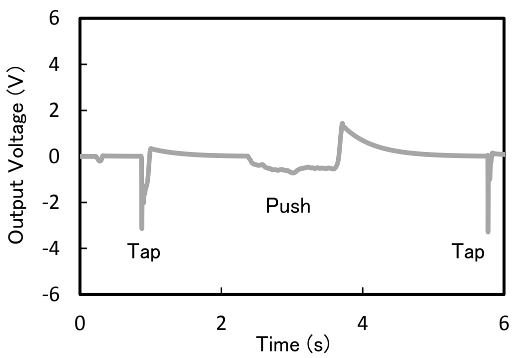


Fig. 12. Vibration wave.

V. CONCLUSION

This paper provides an overview of a multimodal strategy board for goalball and establishes its significance. A method for determining ball position from game video was described and illustrative results were shown. In an evaluation of the proposed ball extraction method, the accuracy rate was found to be approximately 91%, with an extraction rate of roughly 65%. Since the ball could not be detected when it was obscured by a goal post or a player, further steps are needed to improve the accuracy of ball extraction and tracking. The haptic device created for the proposed strategy board was found to be useful in acquiring contact information and generating various vibration waveforms.

In the future, methods for presenting strategic analysis and providing multi-sensory information will be developed. We intend to take the lead in applying these developments to competitive sports played by participants with physical disabilities.

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REFERENCES

[1] X. Wang, V. Ablavsky, H. B. Shitrit, and P. Fua, "Take your eyes off the ball - Improving ball tracking by focusing on team play," *Computer Vision and Image Understanding*, vol. 119, pp. 102-115. 2014.

[2] X. Cheng, X. Zhuang, Y. Wang, M. Honda, and T. Ikenaga, "Particle filter with ball size adaptive tracking window and ball feature likelihood model for ball's 3D position tracking in volleyball analysis," *Lecture Notes in Computer Science*, no. 9, pp. 203-211, 2015.

[3] J. Kurano, M. Hayashi, T. Yamamoto, K. Oshima, M. Tanabiki, and Y. Aoki, "Ball tracking in American football video using information of play initial and terminal points and each player's movement," *Journal of the Japan Society for Precision* , vol. 81, no. 8, pp. 91-98, 2015.

[4] T. Tani, H. H. Huang, and K. Kawagoe, "Sports play visualization system using trajectory mining method," *Procedia Technology*, vol. 18, pp. 100-103, 2014.

[5] J. Ren, M. Xu, J. Orwell, and G. A. Jones, "Multi-camera video surveillance for real-time analysis and reconstruction of soccer games," *Machine Vision and Applications*, vol. 21, pp.855-863, 2010.

[6] G. Gomez, P. H. López, D. Link, and B. Eskofier, "Tracking of ball and players in beach volleyball videos," *PLoS ONE*, pp. 1-19, 2014.

[7] S. Tamaki and H. Saito, "Reconstruction of 3D trajectories for performance analysis in table tennis," *Computer Vision and Pattern Recognition Workshops*, pp. 23-28, 2013.

[8] S. Sakamoto, M. Otake, Y. Hashiguchi, R. Isano, and S. Kanno, "Fundamental analysis of the attack style seen from a distance and shoot angle of blind soccer – At the 2012 London Paralympic Games –," *2014 Biomedical Fuzzy System Association*, pp. 121-122, Tokyo, 2014.

[9] K. Ishikawa, M. Tonishi, H. Endou, and N. Nakamura, "Presentation of the figure using multi-modal information," *IEICE technical report*, vol. 112, no. 374, pp. 1-3, 2013.

[10] M. Ohtsuki, A. Kimura, T. Nishiura, F. Shibata, and H. Tamura, "Design and implementation of anovel method of interacting with mixed reality space," TVRSJ, vol. 13, no. 2, pp. 247-256, 2008.

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