# Human Pointing Navigation Interface for Mobile Robot with Spherical Vision System

Paper:

# Human Pointing Navigation Interface for Mobile Robot with Spherical Vision System

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[Received March 5, 2011; accepted May 9, 2011]

**Human-robot interaction requires intuitive interface that is not possible using devices, such as, the joystick or teaching pendant, which also require some trainings. Instruction by gesture is one example of an intuitive interfaces requiring no training, and pointing is one of the simplest gestures. We propose simple pointing recognition for a mobile robot having an upward-directed camera system. The robot using this recognizes pointing and navigates through simple visual feedback control to where the user points. This paper explores the feasibility and utility of our proposal as shown by the results of a questionnaire on proposed and conventional interfaces.**

**Keywords:** user interface, mobile robot navigation, spherical vision system, pointing gesture

## 1. Introduction

While robot applications in entertainment have enjoyed an explosive popularity, e.g., Sony's AIBO [1] and Aldebaran's Nao [2], more practical mobile robots are also becoming popular, for example, iRobot's Rumba [3] and CCP's SO-ZI [4], which are vacuum cleaners that work automatically without human interaction. More practical robots interacting with general users are expected to become popular in the near future.

Human-robot interaction requires intuitive interfacing. A specific-function interaction device, such as, a joystick or a teaching pendant, is not usually intuitive and requires training for the general user. Instruction by gesture is one example of intuitive interfaces for which a potential user does not need training.

Most conventional studies related to gesture recognition assume that camera height is about that of the human torso [5–10]. This assumption is reasonable for a robot that is as tall as a human. It is not reasonable, however, for a smaller robot such as a vacuum cleaner robot for a general user, for example, Rumba. Another approach to human gesture recognition uses multiple cameras in a room to determine the human posture [11–13]. It provides the precise posture of the human hand and can control a robot based on hand gestures. The cost of building multiple cameras into a room, computing recognition, and communicating between the recognition system and a robot are too high to enable the recognition system to be applied to mobile robot consumer products.

Localization and navigation with an upward-directed camera on a mobile robot has been studied [14, 15], so far. The mobile robot watches ceiling and localizes itself. This has advantages over other vision-based localization, e.g., the ceiling image can be captured with less occlusion than a side view, and it requires less computational cost for localization based on image processing. A ceiling image is mostly only parallel and rotation transforms with less magnification transform while the mobile robot moves on the flat floor. Visual processing can therefore eliminate the image magnification factor. Template matching, for instance, needs less computational cost if it does not have to deal with the image magnification factor.

An upward-directed fish-eye camera has the same advantages as the conventional upward-directed camera-based localization methods and also a wide view angle. The camera simultaneously captures both the ceiling and a human subject as a potential general user, therefore, a robot with an upward-directed fish-eye camera can localize itself with a ceiling image while it recognizes a human gesture.

This paper proposes simple human pointing recognition for a mobile robot with an upward-directed fish-eye camera that recognizes human pointing and navigates itself to the place to which the human subject points with a simple visual feedback controller. The user can navigate the mobile robot intuitively by pointing at a desired position. Real robot experiments and questionnaire investigations with 11 persons in their 20s are conducted to show the feasibility and utility of our proposal.

## 2. Mobile Robot with Spherical Vision System

**Figure 1** shows an omnidirectional vehicle with a spherical vision system consisting of an upward-directed fish-eye camera and cameras with omni-mirrors, which we designed and built. The upward-directed fish-eye camera captures sights higher than the horizon while cameras with omni-mirrors capture sights lower than the horizon. The height of the robot is about 50 cm. The method pro-

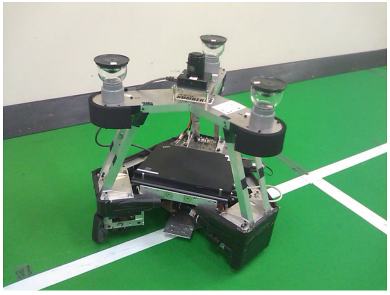


**Fig. 1.** Mobile robot with a spherical vision system consists of an upward directed fish-eye camera and cameras with omni-mirrors.

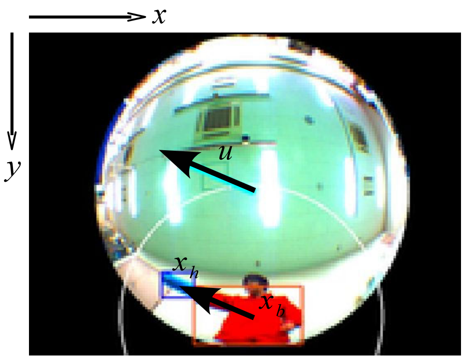



**Fig. 2.** Captured image from upward-directed fish-eye camera and simple visual feedback for navigation.

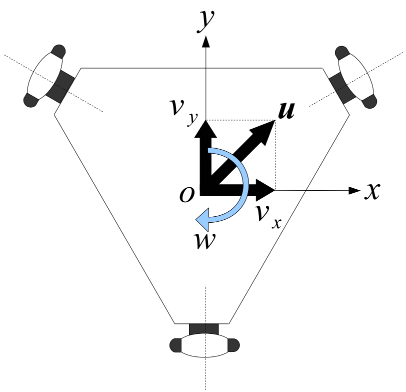



**Fig. 3.** Robot coordinate.

posed in this paper focuses on captured images using the upward-directed fish-eye camera. **Fig. 2** shows captured image. To keep the vision system simple, a human subject wears a red jacket and a blue glove.

**Figure 3** shows a model of our omnidirectional vehicle with three omniwheels. Coordinates $x$ and $y$ indicate the left and front of the robot. The robot has two omniwheels at left and right front and another one at back. It can move toward any direction $v_x, v_y$, including rotation $w$, on a plane.

## 3. Recognition of Human Pointing and Navigation

Human pointing is recognized with a simple algorithm. The vision system extracts red and blue regions on the captured image to recognize the positions of the human torso and hand. To reduce hand recognition error, blue regions within a certain distance of a red/torso region, shown by white circles in **Fig. 2**, are regarded as hand region candidates. The largest region among them is recognized as a hand.

The navigation algorithm is designed as a simple visual feedback. The robot moves to a position so that the hand comes to the human torso region in the fish-eye camera image. The human hand comes to the torso area when the robot is located at the place the human subject is pointing at, as shown in **Fig. 4(e)**. The hand position is far from the torso region when the human points with the hand at a position where the robot is not located, as shown in **Fig. 4(b)**. The intuitive idea leads to a simple visual-feedback-based navigation controller. Movement vector $\boldsymbol{u} = (v_x, v_y)$ for navigation is designed as follows:

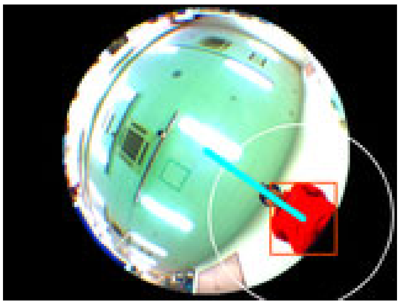
$$\boldsymbol{u} = k(\boldsymbol{x}_h - \boldsymbol{x}_b) \quad \quad (1)$$

while $k$, $\boldsymbol{x}_h$, and $\boldsymbol{x}_b$ are control gain and center position vectors of the extracted human hand and torso on the captured image (**Fig. 2**).[1] An object actually located at the right is projected to the left in a ceiling image and vice versa, so, direction $x$ in a ceiling image is reversed when movement vector $\boldsymbol{u}$ is calculated. In conventional image processing, the $y$ coordinate is set from top to down as shown in **Fig. 2**. The $y$ coordinate is simply flipped upside down to follow the robot coordinate shown in **Fig. 3**. This means that the upper and right directions in the camera image correspond to forward and left in robot coordinates.

The controller designed using Eq. (1), however, has low operability where the robot goes far from the user. The region of the user in the image captured by the upward-directed fish-eye camera becomes smaller if the user is farther from the robot. This means Eq. (1) gives a smaller movement vector when the user is farther from the robot, whereas it becomes larger when the user is nearer to the robot. To compensate for the length of the movement vector based on the distance from the robot and the user, the movement vector is magnified based on the scale of the user region in the image. If the user is projected as small in the image, the image is virtually magnified so that the user region in the image becomes the same size as the user region projected in the image when the user is near the robot. This means that the user size in the image is kept virtually as constant so that the length from the torso and the hand of the user keeps constant if the user shows exactly the same gesture pointing to the robot. Concrete adaptive gain control is designed as follows:

$$\boldsymbol{u} = k\frac{f(S_{\max})}{f(S)}(\boldsymbol{x}_h - \boldsymbol{x}_b) \quad \quad (2)$$

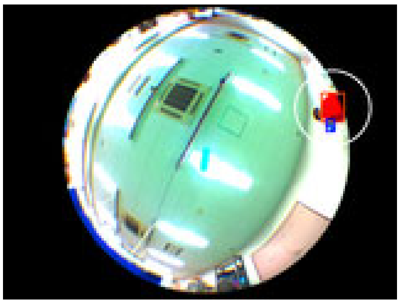
1. Rotation speed $w$ is fixed to zero because it is not directory related to the navigation in experiments.



(a)

(b)

(c)



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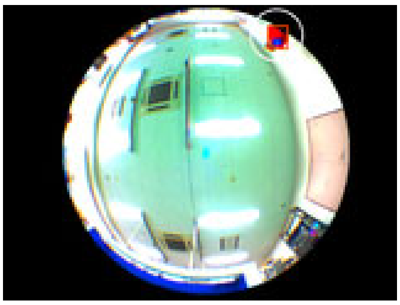


(e)

**Fig. 4.** Images from the upward-directed fish-eye camera.

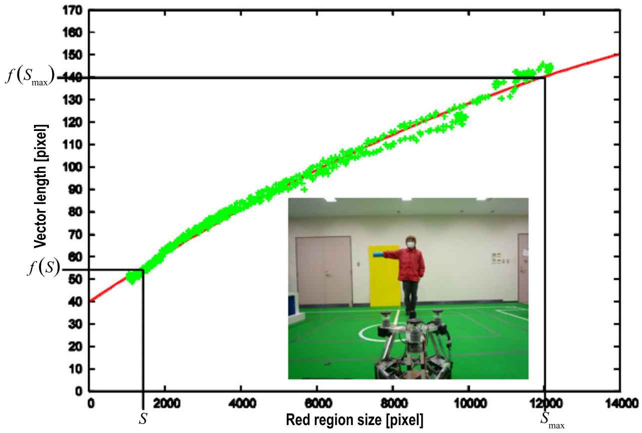



**Fig. 5.** Relationship between red region size and length of vector between red and blue regions.

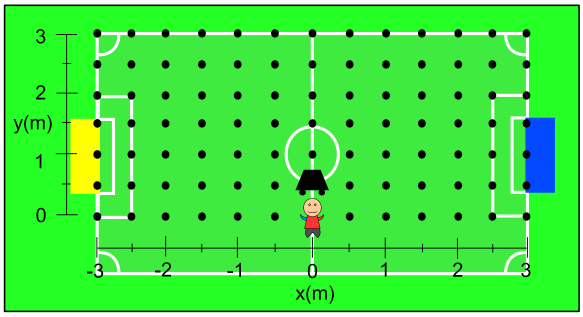



**Fig. 6.** Experimental setup for evaluation of human pointing navigation.

where $S$, $S_{\max}$, $f(S)$ are the red region size in the current image, the red region size when the user stands nearest to the robot, and the length of the vector between the red (torso) and blue (hand) regions. $\frac{f(S_{\max})}{f(S)}$ magnifies the moving vector as long as the user stands nearest the robot. Data on the relationship between the red region size and the length of the vector between red and blue regions when the user is pointing horizontally as shown at bottom right in **Fig. 5** is collected beforehand. Data is approximated with the function in Eq. (3):

$$f(S) = aS^2 + bS + c \quad \ldots \ldots \ldots \ldots \quad (3)$$

Parameters $a$, $b$, and $c$, of function $f(S)$ are tuned based on data. **Fig. 5** shows data and the function with tuned parameters.[2]

## 4. Performance Evaluation of Human Pointing Navigation

The control performance of the proposed human pointing navigation is evaluated first of all. Experiments are conducted on a small soccer field. **Fig. 6** shows the exper-

2. $a = -0.000000234337$, $b = 0.0111673$, $c = 39.9448$

imental setup. A human subject stands at $(0,0)$ depicted in **Fig. 6** and faces the opposite sideline. The human subject points with the right hand at one point on one of the dots depicted in **Fig. 6**. An omnidirectional mobile robot with an upward-directed fish-eye camera recognizes the human subject pointing and navigates to the place pointed to. Errors between the place pointed to and the robot destination are recorded.

**Figure 7** shows how the robot works with human pointing. While the human subject does not show the hand to the robot, the robot stays around the human subject (**Fig. 7(a)**). When the human subject points with the right hand at a certain point on the field, the robot recognizes the hand and torso region in the fish-eye camera image and moves successfully to the point (**Figs. 7(b)–(e)**).

To evaluate navigation performance, the error between the query point and the location that the navigated robot reaches is investigated. The human subject points at one of the dots depicted in **Fig. 6**. The size between the dots is 0.5 m by 0.5 m. **Fig. 8** show the query points on the field and the final locations to which the robot navigated based on the controller with adaptive gain control. Crosses indicate the query points and heads of arrows indicate the final locations that the robot navigated.

The error becomes small when the query point is close to the pointing user because the pointing vector is detected as large while the robot is close to the human subject. The controller with adaptive gain control shows smaller errors in region $[-2\text{ m}, 2\text{ m}]$ horizontally. Error exceeds 0.5 m, unfortunately, if the place pointed to is more than 2 m from the user. The reason for this is that the red (torso of the user) region in the image becomes too small when the robot goes too far from the user to compensate for the moving vector.

The errors on the right side on the field are smaller than the ones on the left side. One of the reasons for this is that the projection of the human right hand onto the fish-eye camera image tends to be smaller when the human subject points to left side of the field. Another reason for this is that the center of the torso is not proper position of origin of the moving vector as described in Eqs. (1) and (2). The position of the right shoulder should, actually, be the position of the origin when the user points with the right hand. When the user points to the right side, the center of the torso is close to the position of the right shoulder but it becomes far away if the user points to the left side.

**Figure 9** shows a comparison of the error rate between adaptive gain control and fixed gain control. The user stands at $[0\text{ m}, 0\text{ m}]$ on the field and points to $[0\text{ m}, 1\text{ m}]$ with the right hand. The robot starts to navigate to the point from one of the points depicted with gray crosses. It is apparent that adaptive gain control leads the robot to a more accurate point than fixed gain control, which shows larger errors vertically because the size of the vector on the projected image seen by the fish-eye camera, that is, $\boldsymbol{x}_h - \boldsymbol{x}_b$ in Eqs. (1) and (2), tends to be too small to lead the robot to the query point. Adaptive gain control, however, compensates for this effect by tuning gain accordingly.

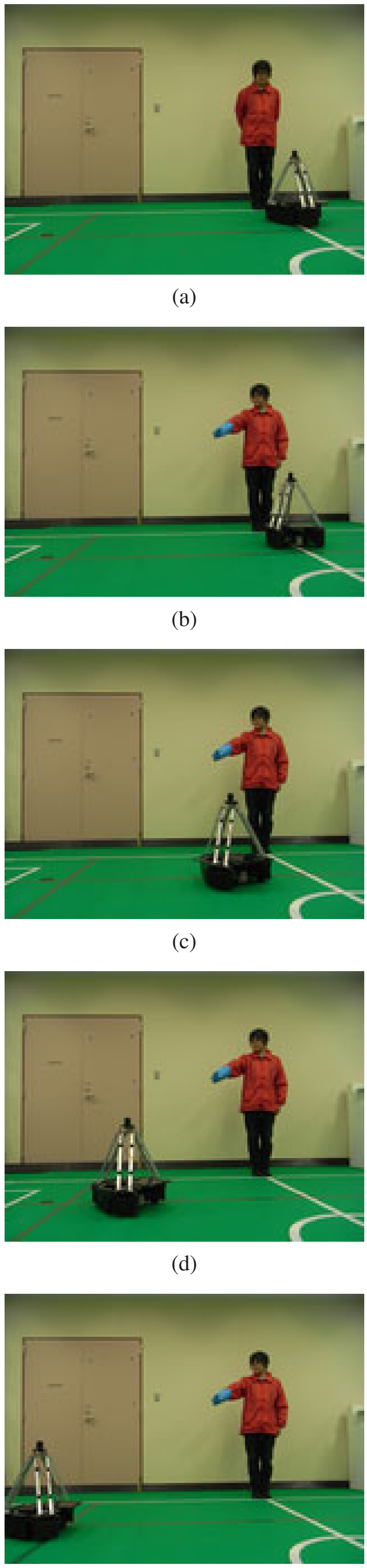



**Fig. 7.** Human pointing and navigation.

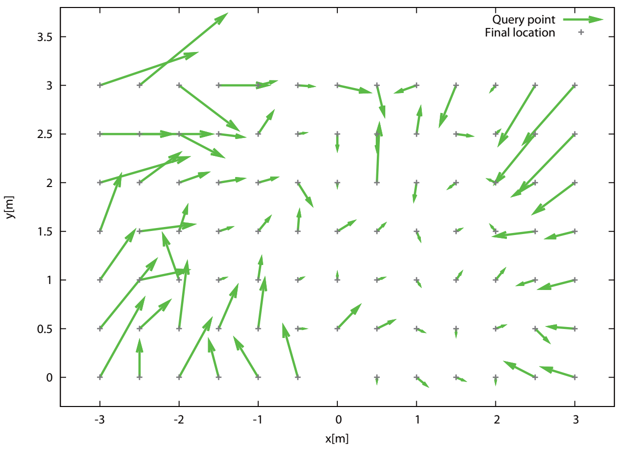
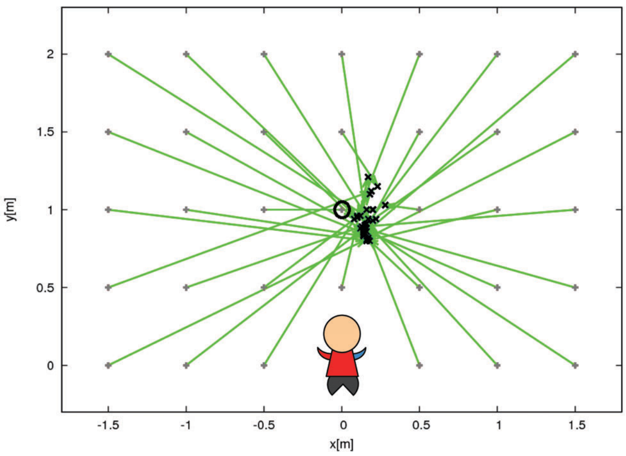
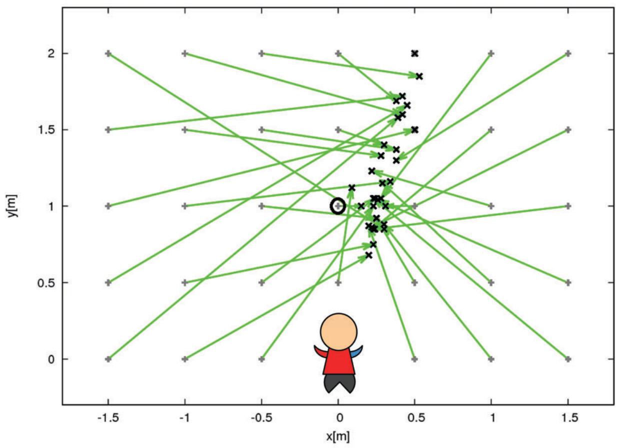



**Fig. 8.** Navigation errors with adaptive gain control.




(a) adaptive gain




(b) fixed gain

**Fig. 9.** Errors with adaptive/fixed gain control during navigation to a fixed point.

## 5. Human Pointing Navigation

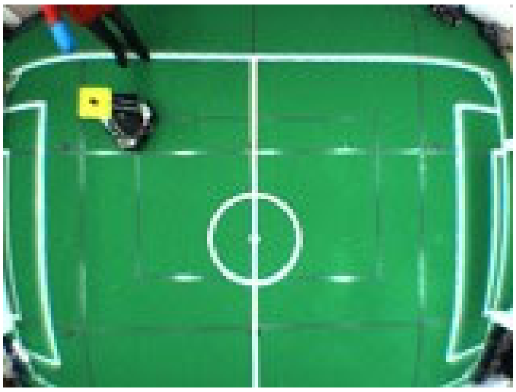
Another experiment is conducted to evaluate real-time navigation by a human subject pointing. The human subject navigates the robot by pointing with the hand on lines of a rectangle drawn on a soccer field. The rectangle is 2.6 m by 1.7 m in size. A camera on a ceiling above the field records the trajectory of the robot while the human subject navigates it. The ceiling camera is used only for recording, not for control or navigation. To detect the robot position on the field, the robot wears a yellow marker on top and the ceiling vision system estimates the position by extracting the yellow region. A fish-eye lens on the camera captures wide range of the field. An undistortion map is calculated before recording the robot trajectory to acquire accurate position estimation. **Fig. 10** shows an example in which the robot follows the human subject pointing and runs along the lines of a rectangle. The human subject points to a place on the lines of the rectangle and the robot follows the pointing in real time. The pointing human subject walks around the rectangle while pointing to a line on the rectangle. The subject's walking speed is about 0.25 m/sec.

**Figure 11** shows an example of a trajectory of the navigated robot. The human subject navigates the robot so that it walks on the rectangle 6 times. Black line indicates lines on the rectangle and gray line indicates the trajectory of the robot. The robot follows the human subject pointing accordingly overall although it sometimes overshoots over the lines. Navigation error is less than 0.6 m and the robot width is 0.5 m. A more sophisticated navigation controller could improve performance while the current one uses a simple feedback controller, although the current performance is reasonable, for instance, for a daily-use home cleaning robot.

## 6. Usability Evaluation of Human Pointing Navigation

To evaluate the utility of the proposed human pointing navigation, a questionnaire filled out by 11 persons in their 20s was conducted. We prepared 4 methods for robot navigation: pointing with fixed control gain, pointing with adaptive gain control (**Fig. 12(a)**), joystick control (**Fig. 12(b)**), and game-pad control (**Fig. 12(c)**). A subject is asked to navigate the robot as desired with one of the methods above for about half a minute to get used to the method. After getting used to the method, the subject navigates the robot along a 2.1 m by 1.5 m rectangle on the soccer field for about one minute. The subject repeats this procedure for all methods, then, fills out the questionnaire as follows:

- Amusement: no fun (1) — fun (5)
- Operability: hard (1) — easy (5)
- Favorite: dislike (1) — like (5)



(a)

(b)

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(d)

**Fig. 10.** Human pointing following.

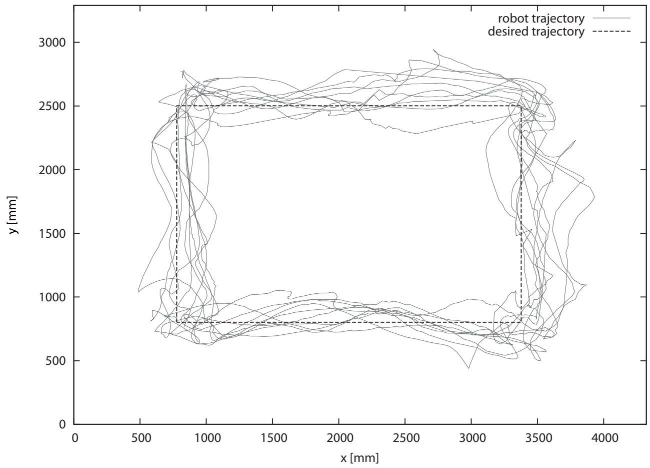


**Fig. 11.** Trajectory during human pointing following.

(a) Pointing

(b) Joystick

(c) Game-pad

**Fig. 12.** User interfaces.

**Figures 13–15** show questionnaire results. Vertical axes indicate the number of votes for each degree from 1 to 5 of the items – amusement, operability, and favorite. Most subjects are used to the gamepad because they sometimes play computer games but are not used to the joystick. They feel fun with the joystick and pointing with fixed/adaptive control gain because these are new

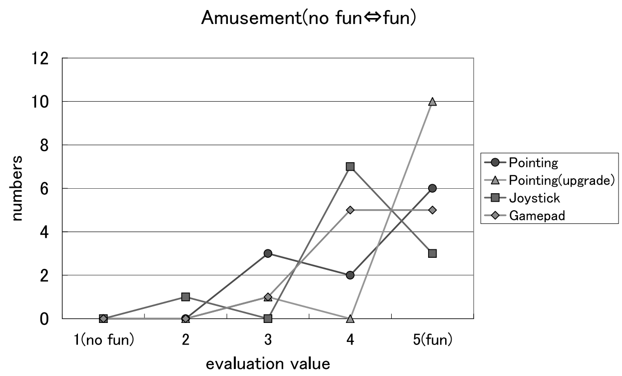


**Fig. 13.** Questionnaire result: amusement.

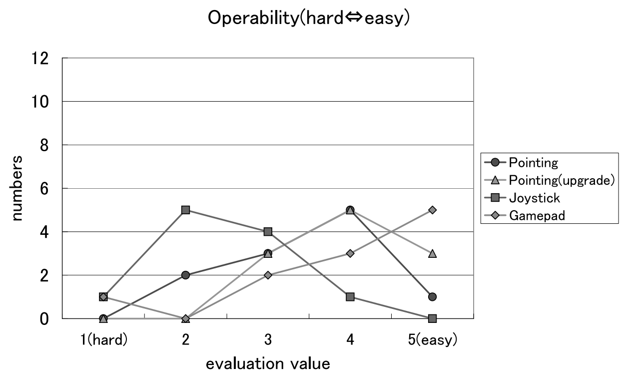


**Fig. 14.** Questionnaire result: operability.

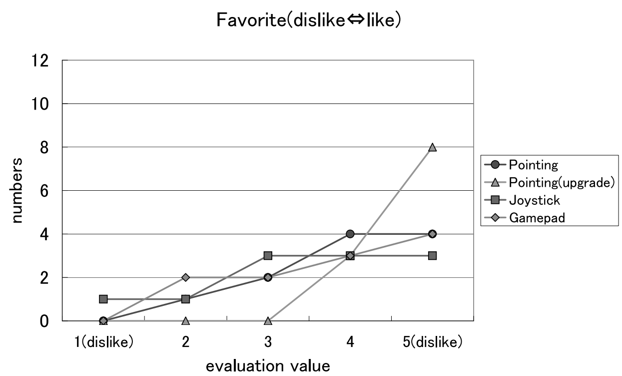


**Fig. 15.** Questionnaire result: favorite.

experiences for them. They find it difficult to navigate the robot with the joystick and pointing with fixed control gain because they are not used to the joystick and pointing with fixed control gain makes the robot behave in different ways depending on the distance from the robot to the user. The gamepad shows the best operability because subjects are used to it and pointing with adaptive control gain shows the second best. Pointing with adaptive control gain eventually became the most favorite evaluation over all. The reason for this is because subjects enjoy the new experience and the good operability although they are not used to the pointing navigation interface.

## 7. Conclusions and Future Work

We have proposed a simple human pointing recognition system for a mobile robot and investigated the feasibility and utility with a real robot. Our mobile robot with an upward-directed fish-eye camera recognizes a human subject's pointing and navigates to the place that the human subject points. The human subject can navigate the mobile robot intuitively by simply pointing with the hand at desired position on a field. Experimental results show that the proposed method works reasonably well and the user can control and navigate the robot intuitively. Adaptive control gain works well to reduce the differing behavior of the robot based on the distance from the robot and the pointing user and increases the operability and favorable attitude of the user.

The current method requires a potential user to wear a bright uniform-color jacket and glove for them to be detected by simple color extraction processing in a vision system. It is not convenient for the user to wear such outfits every time the user navigates the robot, so a method extracting the user region in the upward-directed fish-eye camera image should be developed.

Currently, a potential user must continue pointing at a desired position until a robot reaches it. As future work, the proposed method will be extended so that the robot estimates the direction and distance of the place pointed to from a captured image of the pointing user. Nagai et al. [16] proposed a "joint attention" model that enables the robot to look at an object that its user is watching. Their model trains a map from a user's face camera image to input to head direction control. A similar idea may be applicable for our purposes, that is, a mobile robot learns a map from the captured image of a pointing user for the direction and distance of the place pointed to.

Another future work may be the extension of the proposed method to more complex tasks including execution order. A potential user instructs the robot, for example, to bring Object A from Room B to Room C. The current method requires the user to point to the object and the rooms continuously while the robot executes the task. Gesture recognition helps the user with the instruction of the task effectively and sophisticatedly.

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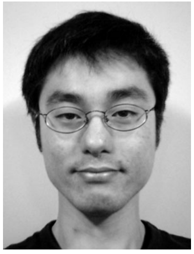

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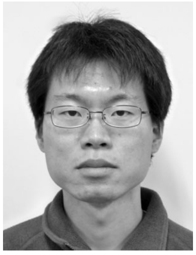

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**Main Works:**

• Y. Maeda, M. Tanabe, and T. Takagi, "Behavior-Decision Fuzzy Algorithm for Autonomous Mobile Robots," Information Sciences, Vol.71, No.1, pp. 145-168, 1993.
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**Membership in Academic Societies:**

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• The Robotics Society of Japan (RSJ)
• Japan Society for Fuzzy Theory and Intelligent Informatics (SOFT)
• The Japanese Society for Artificial Intelligence (JSAI)
• Japan Society of Kansei Engineering (JSKE)