Quick Realization of Function for Detecting Human Activity Events by Ultrasonic 3D Tag and Stereo Vision

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Abstract

This paper proposes quick functions for setting up an ultrasonic tagging system for the detection of object handling as part of daily human activities. The system provides robust measurement of the three-dimensional position of objects and robust detection of registered events in real time, and is supported by fast calibration and event registration procedures. The system detects object manipulation in real time using ultrasonic tags attached to objects and a robust position-estimation algorithm known as random sample consensus (RANSAC). Calibration of sensor position is achieved using a calibrating device fitted with only 3 or 4 sensors, and can be used to calibrate an area of arbitrary size quickly and simply, making the system readily portable. Registration of target activities is performed by the user using interactive software linked to a stereoscopic camera fitted with ultrasonic tags. The user creates simplified models of the objects, attaches virtual sensors, and associating the virtual sensors with the target events.

1. Introduction

Information processing services centered around human activity in the real world have attracted increased attention recently [1]. Human-centered applications require the facility to observe and recognize activities as a basis, and the present paper describes a method for quickly setting up a system for robustly detecting daily human activity events in the real world.

Generally, the problem of human activity recognition can be formulated as a kind of pattern recognition problem as follows.

$$P(\hat{W}|Y) = \max_{W_i} \frac{P(Y|W_i)P(W_i)}{P(Y)}, \quad (1)$$

where $P(W_i|Y)$ denotes the posterior probability that the meaning of an observed behavior pattern Y is W_i, $P(Y)$ denotes the probability that a behavior pattern Y will be observed, $P(W_i)$ denotes the probability that the behavior meaning W_i will occur, and $P(Y|W_i)$ denotes the conditional probability. Thus, the problem of human activity recognition becomes a search for the maximum posterior probability $P(\hat{W}|Y)$.

There are three problems in realizing and utilizing a function for recognizing human activity in the real world: the robust observation of an activity pattern Y, the efficient recognition of meaning W from the observed pattern, and quick implementation of a system for robustly observing and efficiently recognizing human activity. Without solving the first problem, equation (1) cannot be formed. Without tackling the second problem, guaranteeing a solution to the equation within the timeframe demanded by the application is impossible, and without dealing with the third problem, it is difficult to utilize any system in real applications or research.

As a method for efficient recognition of activities, the idea of object-based activity recognition has been proposed [2]. In theory, the behavior of handling objects in an environment such as an office or home can be recognized based on the motion of the objects. However, when applying the method to real environments, it is difficult to even achieve an adequate level of object recognition, which is the basis of the method.

Separating the problems of object recognition and activity recognition is becoming increasingly realistic with the progress in pervasive computing technology such as microcomputers, sensors, and wireless network technology. It has now become possible to resolve object recognition into the problems of sensorizing objects and tagging the objects with identification codes (IDs), and to address activity recognition separately through the development of applied technology.

The present authors have developed a three-dimensional (3D) ultrasonic location and tagging system as a fundamental system for robustly tracking objects. This system introduces a new approach to tag-based activity recognition. In terms of cost and robustness against environmental noise, the ultrasonic system is superior to other location techniques such as visual, tactile, and magnetic systems. Although a number of ultrasonic location systems have already been proposed or commercialized [3, 4, 5], no method has been developed for improving the robustness, accuracy, and resolution of position when a person handles objects tagged with ultrasonic location sensors. Although Shih [4] proposed a robust estimation method by "direct substitution", the system had difficulty in maintaining the accuracy of position and calculation in real time. The system presented in the present paper has been developed specifically to address the issue of robustness and accuracy in real time when a person handle objects tagged with ultrasonic location sensors.

This paper focuses specifically on some supporting tools that can be used to set up a system for robustly detecting daily human activity events quickly. Based on the fundamental ultrasonic tagging system for robustly measuring the 3D position of objects handled by a person, quick methods for the calibration of sensor position and the user registration of target activity events are introduced. The next section describes the system for detecting human activity events. Section 3 presents and evaluates the algorithms employed for robustly measuring the 3D position of objects handled by a person. Section 4 describes the quick calibration method, and section 5 presents the quick registration scheme for human activity based on stereoscopic video with ultrasonic tags and interactive software.

2. System for Detecting Human Activity Events

This section describes the system for robustly observing and efficiently recognizing daily human activities.

2.1. Overview

The configuration of the proposed system is shown in Fig. 1. The system consists of an ultrasonic tag system, a calibration device, a stereoscopic camera with ultrasonic tags, and a host computer. The system provides four key functions: robust measurement of the 3D position of objects (Fig. 1(A)), quick calibration of sensor position (Fig. 1(B)), quick registration of target activity events (Fig. 1(C)), and robust detection of registered events in real time (Fig. 1(D)).

The system realizes robust measurement of the 3D position of objects through the use of an ultrasonic tagging system and robust estimation algorithm known as random sample consensus (RANSAC). Quick calibration is achieved through the use of a calibration device with three or more ultrasonic transmitters, making the system portable. Quick registration of target activity events is realized through the use of a stereoscopic camera with ultrasonic tags and interactive software for creating a 3D shape model. In registration, simplified models of objects are defined and assigned virtual sensors, and the virtual sensors are then associated with target events.

2.2. System setup

The steps required to establish the basic detection system are outlined below.

1. Install ultrasonic receivers in the target environment.
2. Calculate the 3D position of installed ultrasonic receivers using a calibration device (see section 4 for details).
3. Register target activity events using a stereoscopic camera with ultrasonic tags and interactive software (see section 5 for details).
4. Detect the registered target events using the ultrasonic tags and virtual sensors.

2.3. Advantages of the Proposed System

The advantages of the proposed system can be summarized as follows.

- **Utilization of user knowledge** Users know the target activity to be detected, and the system can make full use of this knowledge by registering target events interactively.

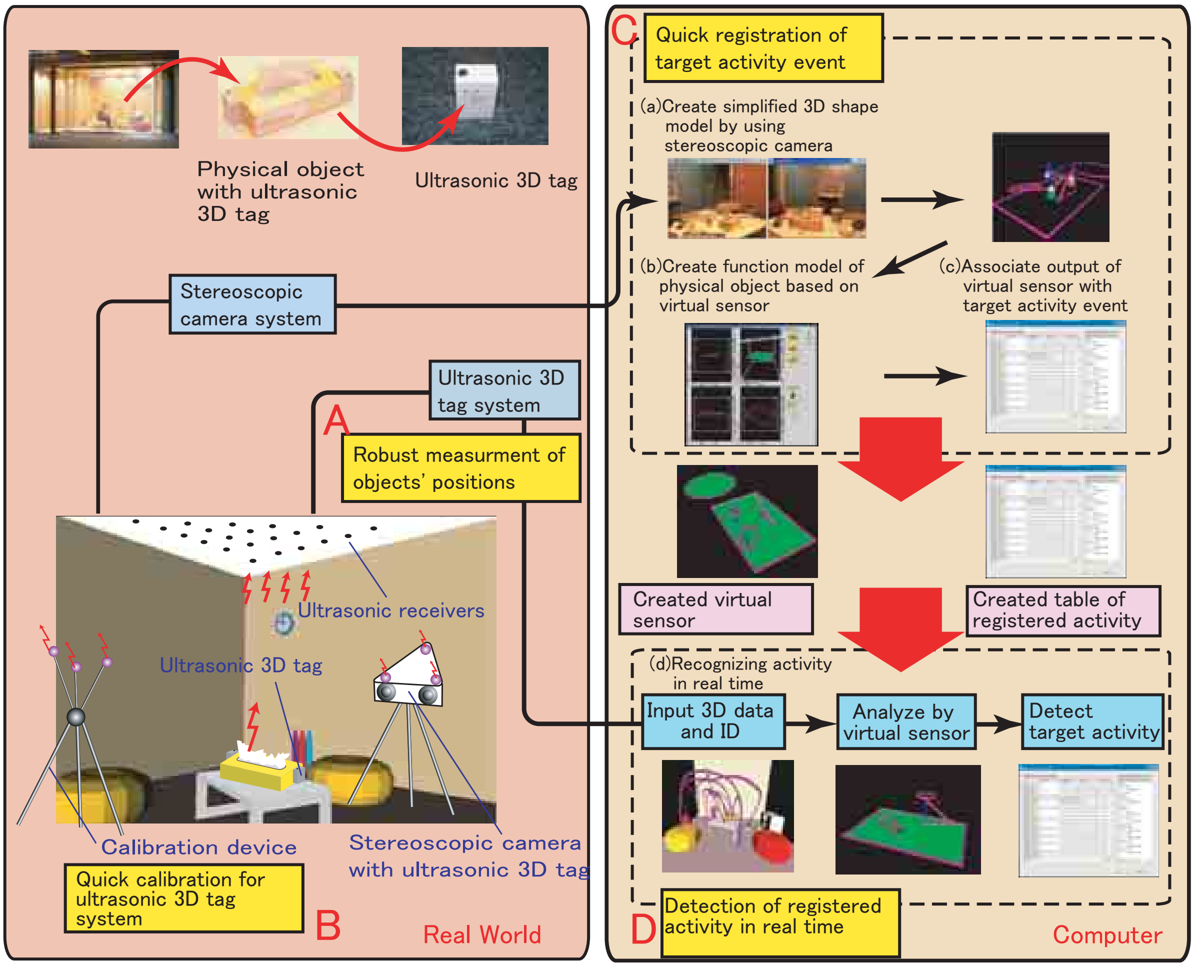

Figure 1. Configuration of system for detecting human activity events

- **Efficient processing** It is possible to minimize the system based on the number of ultrasonic receivers and target events considering also the installation environment and the activity events to be detected.

- **Inexpensive** It is possible to utilize inexpensive sensors such as ultrasonic tags (about \$45 per sensor and \$200 per tag). The stereoscopic camera (about \$200) is also inexpensive.

- **Robustness** The low cost of the sensors means that the number of ultrasonic receivers can be readily increased to ensure robust location ability (see section 3 for details).

- **Ease of improvement** The function for quick registration of target events allows the constructed system to be easily improved by trial and error.

3. Robust Observation of Human Activity in Handling Objects

3.1. Configuration of Ultrasonic Tagging System

Figure 2 shows the configuration of the ultrasonic tagging system. The system consists of an ultrasonic reception section, an ultrasonic transmission section, a time-of-flight measurement section, a network and personal computer. The ultrasonic reception section receives ultrasonic pulses emitted from the ultrasonic transmitter and amplifies the received signal. The time-of-flight measurement section records the travel time of the signal from transmission to reception. The network synchronizes the system and collects time-of-flight data from the ultrasonic reception section. The positions of objects are calculated based on three or more time-of-flight results, which are obtained at a sampling frequency of 50 Hz.

The ultrasonic tagging system calculates the 3D position of an object by trilateration using three distance mea-

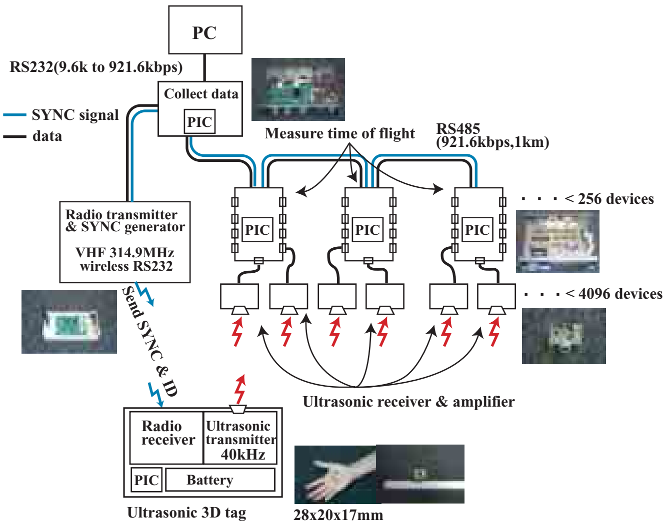

Figure 2. Configuration of ultrasonic tagging system

Figure 3. Experimental living space

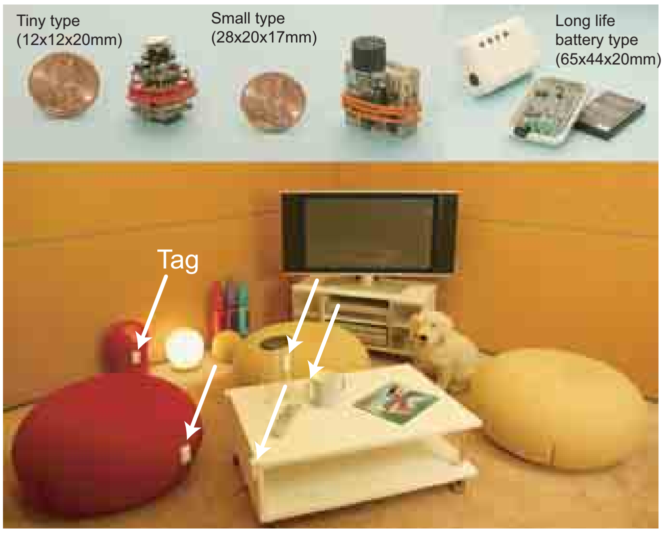

Figure 4. Ultrasonic tags and example of attaching tags to objects

surements. Two methods of multilateration are investigated for use with the proposed system: multilateration based on a least-squares method using redundant distance data, and multilateration based on robust estimation.

The room used to conduct the experiments is shown in Fig. 3. The room was $3.5 \times 3.5 \times 2.7$ m in size, and was fitted with 307 ultrasonic receivers embedded in the wall and ceiling. Tags were attached to various objects, including a cup and a stapler as shown in Fig. 4. Some objects were fitted with two transmitters. The purpose of the experimental room was to clarify the effect of the use of redundant sensors and it should be noted that the algorithms presented in the next section function efficiently with much fewer than the 300 sensors fitted in the experimental room in this case.

3.2. Multilateration method 1: linearization of a minimization problem

Trilateration or multilateration algorithms have been proposed in the field of aerospace [6, 7]. This paper presents some multilateration algorithms that are applicable to a more general case to deal with ultrasonic receivers placed in arbitrary locations. Using distance data l_i, l_j and the receiver positions $(x_i, y_i, z_i), (x_j, y_j, z_j)$, the following spherical equations can be obtained for the possible position of the target.

$$
\begin{aligned}
(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2 &= l_i^2, \quad (2)\\
(x_j - x)^2 + (y_j - y)^2 + (z_j - z)^2 &= l_j^2. \quad (3)
\end{aligned}
$$

By subtracting Eq. (3) from Eq. (2), we obtain an equation for intersecting planes between the spheres, as shown in Fig. 5.

$$
\begin{aligned}
&2(x_j - x_i)x + 2(y_j - y_i)y + 2(z_j - z_i)z = \\
&\quad l_i^2 - l_j^2 - x_i^2 - y_i^2 - z_i^2 + x_j^2 + y_j^2 + z_j^2 \qquad (4)
\end{aligned}
$$

Inputting pairs of (i, j) into the above equation gives the following linear simultaneous equations.

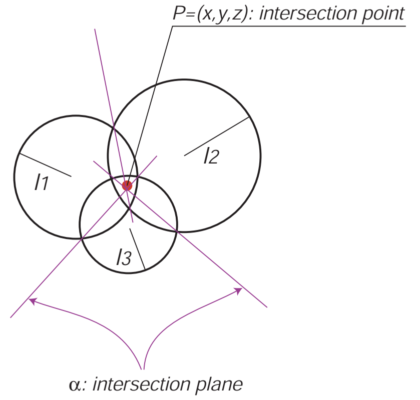

Figure 5. Planes of intersection between spheres for position estimation

$$
\boldsymbol{AP} \;=\; \boldsymbol{B}, \tag{5}
$$

$$
\text{where} \quad \boldsymbol{P} \;=\; \begin{pmatrix} x \\ y \\ z \end{pmatrix}, \tag{6}
$$

$$
\boldsymbol{A} \;=\; \begin{pmatrix} 2(x_0 - x_1) & 2(y_0 - y_1) & 2(z_0 - z_1) \\ 2(x_0 - x_2) & 2(y_0 - y_2) & 2(z_0 - z_2) \\ 2(x_0 - x_3) & 2(y_0 - y_3) & 2(z_0 - z_3) \end{pmatrix}, \tag{7}
$$

$$
\boldsymbol{B} \;=\; \begin{pmatrix} l_1^2 - l_0^2 - x_1^2 - y_1^2 - z_1^2 + x_0^2 + y_0^2 + z_0^2 \\ l_2^2 - l_0^2 - x_2^2 - y_2^2 - z_2^2 + x_0^2 + y_0^2 + z_0^2 \\ l_3^2 - l_0^2 - x_3^2 - y_3^2 - z_3^2 + x_0^2 + y_0^2 + z_0^2 \\ \vdots \end{pmatrix} \tag{8}
$$

The position $(\hat{x}, \hat{y}, \hat{z})$ can then be calculated by a least-squares method as follows.

$$
\boldsymbol{P} \;=\; (\boldsymbol{A}^T\boldsymbol{A})^{-1}\boldsymbol{A}^T\boldsymbol{B}. \tag{9}
$$

This method minimizes the square of the distance between the planes expressed by Eq. (4) and the estimated position. The algorithm is described in detail in Fig. 6. In actual usage, the rank of matrix $\boldsymbol{A}$ must be considered.

3.3. Multilateration method 2: Robust estimation by RANSAC

Data sampled by the ultrasonic tagging system is easily contaminated by outliers due to reflections. Method 1 above is unable to estimate the 3D position with high accuracy if sampled data includes outliers deviating from a normal distribution. In the field of computer vision, robust estimation

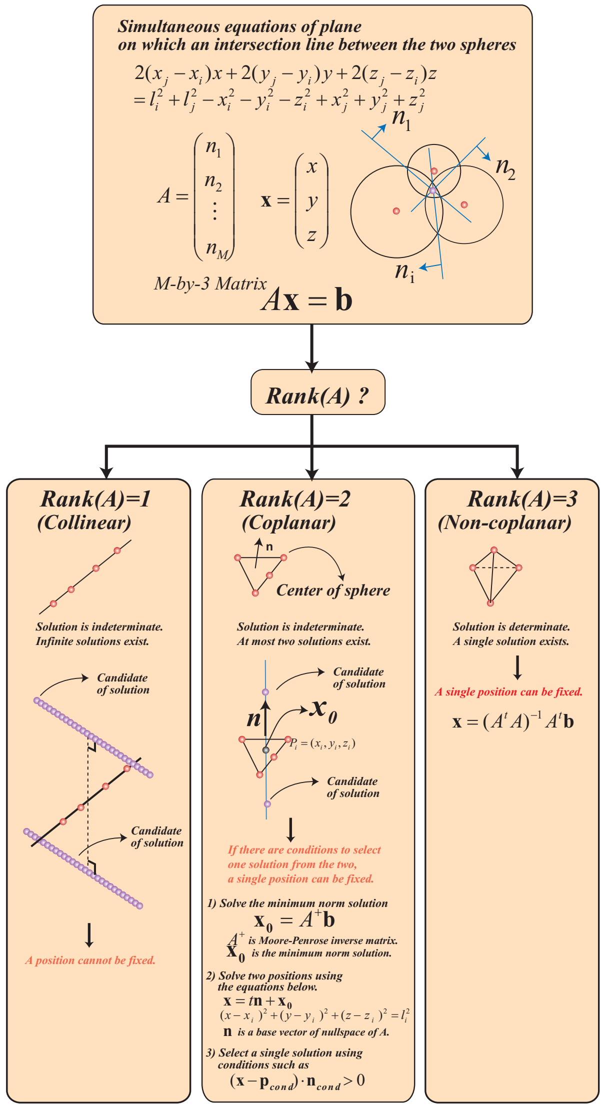

Figure 6. Algorithm for estimating 3D position by a least-squares method considering the rank of A

methods that are effective for sampled data including outliers have already been developed. In this work, the random sample consensus (RANSAC) [8, 9] estimator is adopted to eliminate the undesirable effects of outliers. The procedure is as follows.

1. Randomly select three distances measured by three receivers (jth trial).
2. Calculate the position (x_{cj}, y_{cj}, z_{cj}) by trilateration.
3. Calculate the error ε_{cji} for all receivers ($i = 0, 1, ..., n$) by Eq. (10), and find the median ε_{mj} of ε_{cji}.

4. Repeat steps 1 to 3 as necessary to find the combination of measurements giving the minimum error, and adopt the corresponding 3D position.

$$\varepsilon_{cji} = \left| l_i - \sqrt{(x_i - x_{mj})^2 + (y_i - y_{mj})^2 + (z_i - z_{mj})^2} \right| \quad (10)$$

$$\varepsilon_{mj} = med_j \, |\varepsilon_{cji}| \quad (11)$$

$$(\hat{x}, \hat{y}, \hat{z}) = min \, \varepsilon_{mj} \quad (12)$$

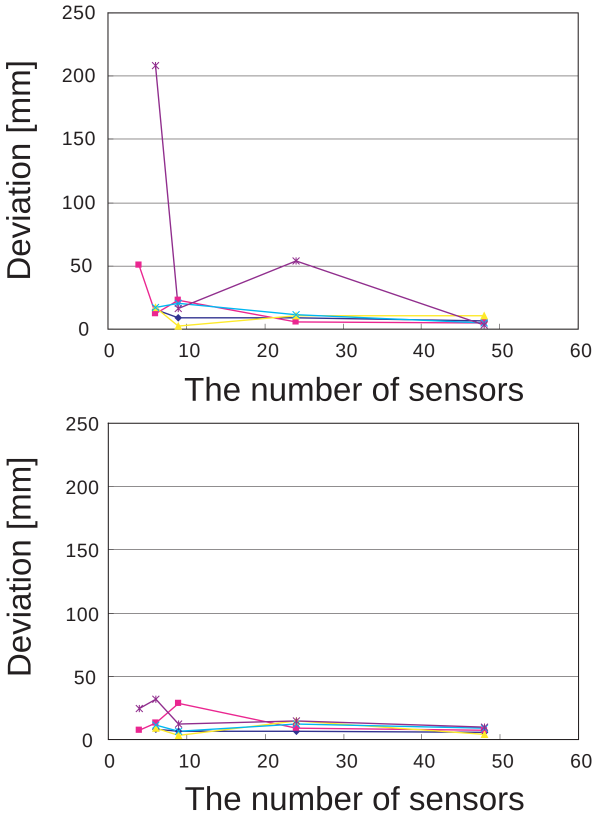

Figure 7. Relationship between resolution and the number of sensors for the least-squares method (upper) and RANSAC (lower)

3.4. Resolution

Figure 7 shows the relationship between the number of receivers and the deviation of the estimated position for 4, 6, 9, 24, and 48 receivers in the ceiling. To compare the effect of the RANSAC method and that of the least-squares method, one receiver is selected randomly and 500 mm is added to the distance data for the selected receiver to represent an outlier. Each point was derived from 30 estimations of the position. The 5 lines in the figures represent the estimations for 5 different locations of the transmitter. The resolution increases with the number of receivers, and the RANSAC method provides a more stable estimation with higher resolution compared to the least-squares method.

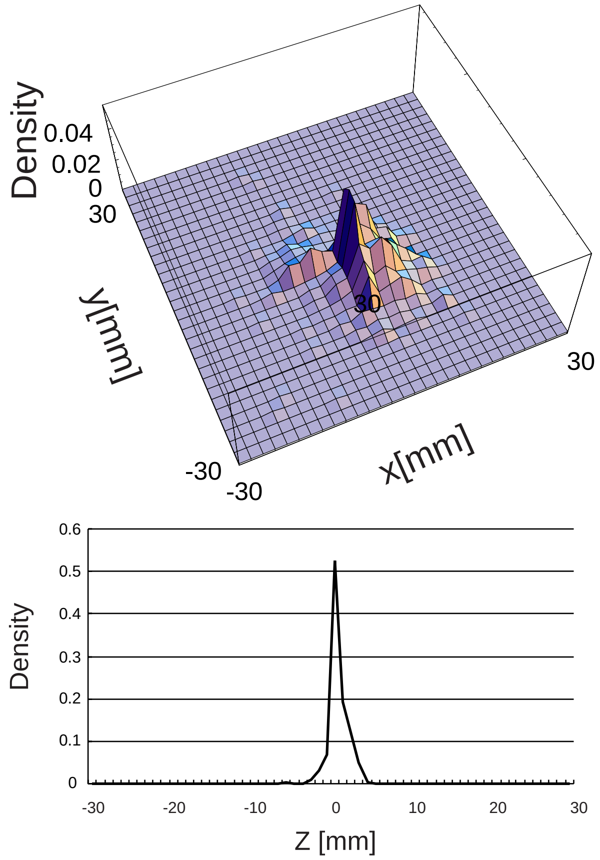

Figure 8. Resolution in the x and y directions (upper) and z direction (lower) (grid size: 2×2 mm)

The resolution in the x, y, and z directions is illustrated in Fig. 8, which shows the probability density distribution for 1000 estimations using RANSAC. The resolution in the x and y directions is about 15 mm, while that in the z direction is about 5 mm.

3.5. Positioning accuracy

Figure 9 shows the relationship between the number of receivers and the error of the estimated position for 4, 6, 9, 24, and 48 receivers. The error is taken as the distance from the position measured by a visual motion capture system.

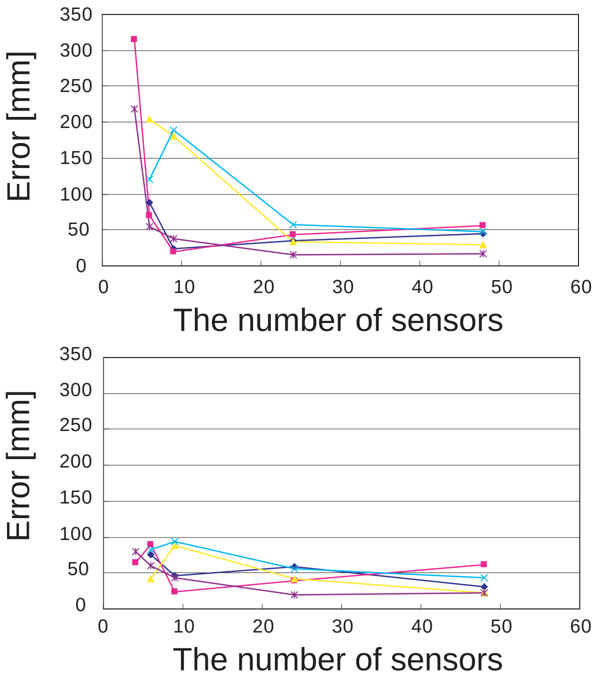

Figure 9. Relationship between positioning accuracy and the number of receivers for the least-squares method (upper) and RANSAC (lower)

One receiver is selected randomly and 500 mm is added to the distance data for the selected receiver as an outlier. Each point was derived from 30 estimations of the position. The 5 lines in the figures represent the estimation for 5 different locations of the transmitter. The error decreases as the number of receivers is increased, and the RANSAC method is appreciably more accurate with fewer receivers. It is considered that the least-squares method is easily affected by outliers, whereas the RANSAC method is not.

Figure 10 shows the 3D distribution of error for 1400 measured positions in the room. The figures show that the error is lowest (20–80 mm) immediately below the 48 receivers in the ceiling, increasing toward the edges of the room.

These results demonstrate that it is possible to improve the accuracy and resolution by increasing the number of receivers, and that the undesirable effect of outliers can be mitigated through the use of RANSAC estimation.

3.6. Robustness to occlusion

As in other measuring techniques such as vision-based methods, it is necessary to increase the number of sensors to solve the problem of sensor occlusion, where the line of sight to the target object is obstructed by other objects such as walls or room occupants. In the present tagging system, the problem of occlusion occurs often when a person moves or operates an object. These situations give rise to two separate problems; a decrease in the number of usable sensors for the target, and an increase in reflections due to obstruction and movement. As one of the most typical situations where occlusion occurs, this section focuses on occlusion due to a hand.

Figure 11 shows how the error increases and the number of usable sensor decreases as a hand approaches an object fitted with an ultrasonic transmitter. The results are shown for both the least-squares and RANSAC methods. Although the error increases significantly by both methods when the hand approaches the object, the RANSAC method is much less affected than the least-squares method. This demonstrates that the proportion of outliers increases when occlusion occurs, and that RANSAC is more robust in this situa-

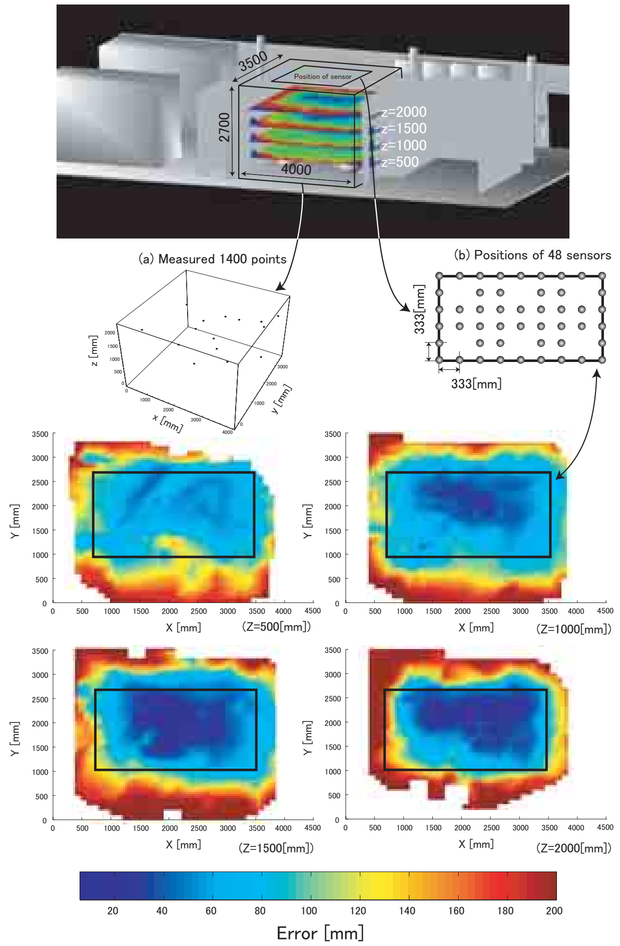

Figure 10. Three-dimensional distribution of error in the experimental room

tion because it can mitigate the effect of such outliers.

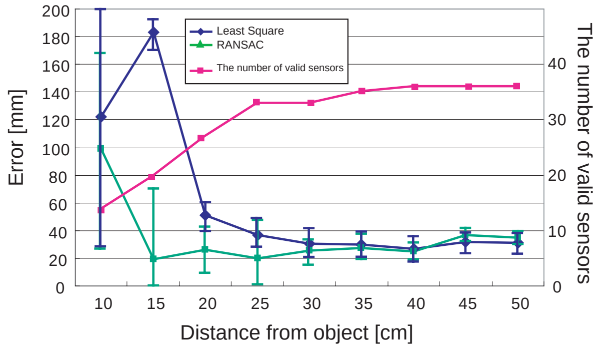

Figure 11. Accuracy of the ultrasonic tagging system when occlusion due to a hand occurs

3.7. Real-time position measurement

Figure 12 shows the measured trajectory for a person moving a cup to a chair, the floor, and a desk. The figure demonstrates that the system can robustly measure the positions of the objects in most places of the room regardless of occlusion by a hand or body.

In the current system, the sampling frequency is about 50 Hz. This frequency decreases to $50/n$ Hz when n objects are being monitored. However, it is possible to maintain a high sampling frequency by selecting which transmitters to track dynamically. For example, a transmitter can be attached to a person's wrist, and the system can select transmitters in the vicinity of the wrist to be tracked, thereby reducing the number of transmitters that need to be tracked at one time and maintaining the highest sampling frequency possible. Figure 13 shows the measured trajectory in a dynamic selection mode. The red sphere in the figure shows the position of the hand.

4. Quick Calibration Method for Ultrasonic 3D Tag System

4.1. Measurement and calibration

The ultrasonic tagging system involves calibration of receiver position and measurement of transmitter position, as shown in Fig. 14. Both problems are essentially the same. As described in the previous section, the robustness of the ultrasonic tagging system can be improved by increasing the number of ultrasonic receivers. However, simple calibration requires a calibration device with a large number of transmitters and which is equivalent in size to the space in which the receivers are fitted, making it difficult to calibrate large volumes. Here, a calibration method that requires a relatively small number of transmitters and which is independent of room size is presented.

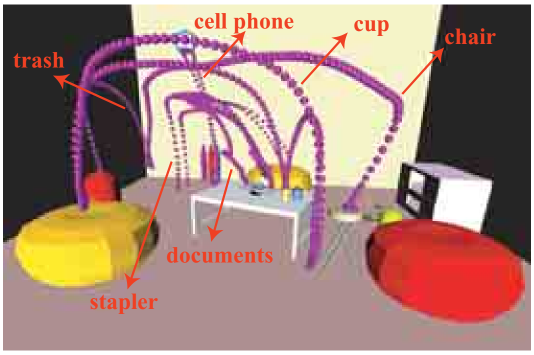

Figure 12. Measured trajectory for movement of several objects one after another

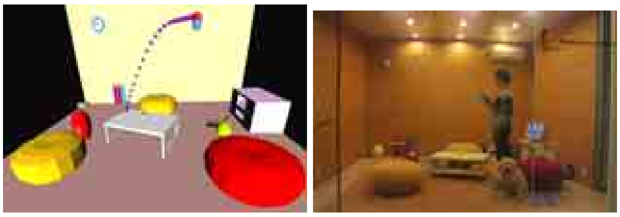

Figure 13. Dynamic selection of transmitters

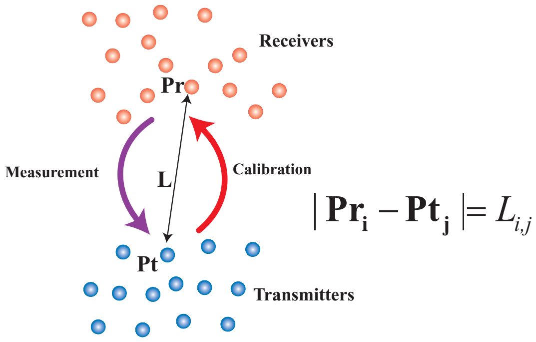

Figure 14. Calibration and measurement

4.2. Quick Calibration Method

The procedure for quick calibration is as follows.

1. Move the calibration device arbitrarily to multiple positions (A, B, and C in Fig. 15).
2. Calculate positions of receivers in a local coordinate system, with local origin set at the position of the calibration system.
3. Select receivers for which the positions can be calculated in more than two positions of the calibration system. The pink points in Fig. 15 denote the points that can be calculated in more than two positions.
4. Select a world coordinate system from the local coordinate systems and calculate the positions of the calibration device in the global coordinate system using the receivers selected in Step 3. Then calculate transformation matrices ($M_1 and M_2$ in Fig. 15).
5. Calculate receiver positions using the receiver position calculated in Step 2 and the transformation matrices calculated in Step 4.

Figure 16 shows the flow of the calibration method.

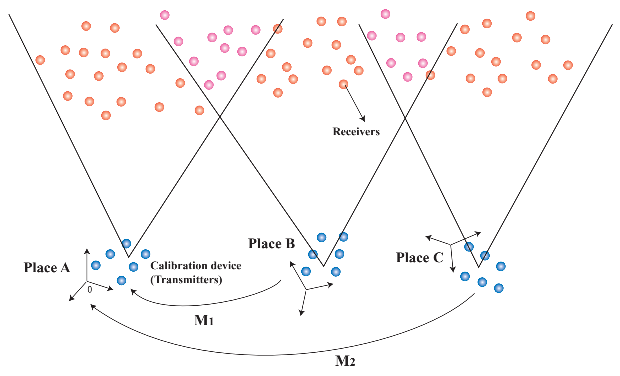

Figure 15. Quick calibration method

4.3. Experimental Results

Figure 17 shows the experimental results. A total of 80 receivers were calibrated using 4 transmitters. The experimental results demonstrate that the proposed calibration method is very effective (maximum positioning error: 103 mm) and can be used in spaces much larger than the calibration system.

The proposed method makes it possible to make the ultrasonic tagging system portable. Figure reffig:calibration-device-pic.eps shows a portable-type ultrasonic tagging system consisting of a case, tags, receivers, and a calibration device. The portable system allows human activities to be measured in the area where the activities occur with quick installation and calibration.

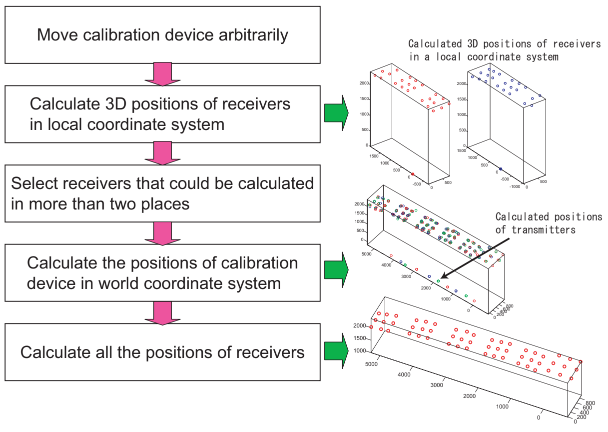

Figure 16. Flow of quick calibration method

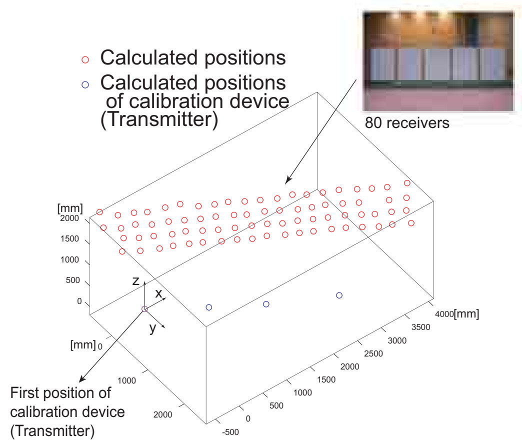

Figure 17. Experimental results for proposed calibration method

5. Quick Registration of Human Activity Events

Quick registration of target human activity events is performed using a stereoscopic camera fitted with ultrasonic tags as shown in Fig. 19 in combination with interactive software. The operation involves simplification of the 3D object and the physical phenomena relating to target events. The software abstracts the shapes of objects in the real world as simple two-dimensional shapes such as lines, circles, or polygons. In order to describe the real-world events when a person handles the objects, the software abstracts the function of objects as simple phenomena such as touch, detouch, or rotation. The software adopts the concept of virtual sensors and effectors to allow the user to define the

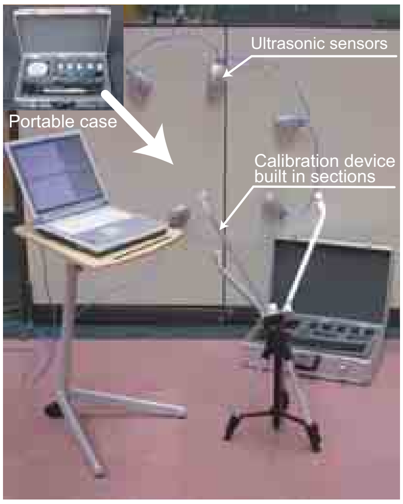

Figure 18. Portable ultrasonic taggin system

Figure 19. Ultravision (stereoscopic camera with ultrasonic tags) for creating simplified 3D shape models

function of the objects easily through simple mouse operations.

For example, to define the activity ”put a cup on the desk”, the user simplifies the cup and the desk as simple two-dimensional models of a circle and rectangle using the photo-modeling function of the software. Using a function for editing virtual sensors, the user then adds a ”touch” virtual sensor to the model of the desk, and adds a ”bar” effector to the model of the cup.

5.1. Software for Quick Registration of Human Activity Events

(a) Creating simplified models of objects Figure 21 shows examples of simplified models of objects such as a tissue, a cup, a desk and a stapler. The cup is expressed as a circle and the desk as a rectangle. The simplification is performed using a stereoscopic camera fitted with ultrasonic tags in combination with photo-modeling software. The camera is fitted with multiple ultrasonic tags, allowing the system to track its position and posture. Therefore, it is possible to move the camera freely while the user creates simplified models, and the system can integrate the created models into the global coordinate system.

(b) Creating models of object functions using virtual sensors/effectors The software creates a model of an object’s function by attaching virtual sensors and effectors to the model created in step (a). Virtual sensors and effectors are prepared in advance by the software and function as sensors and effects affecting the sensors. The current system has an ”angle sensor” for detecting rotation, a ”bar effector” to represent touch, and a ”touch sensor” for detecting touch. In the right part of Fig. 22, red indicate a virtual bar

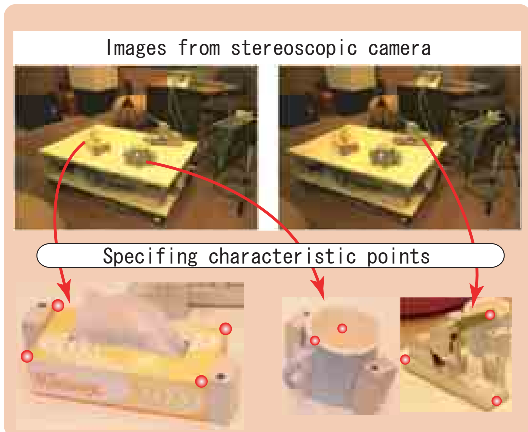

Figure 20. Photo-modeling using the stereoscopic camera system

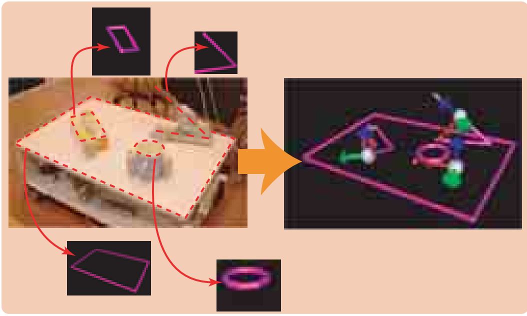

Figure 21. Simplified shape models

effector, and green indicates a virtual touch sensor. Using simple mouse operations, it is possible to add virtual sensors/effectors to the 3D shape model.

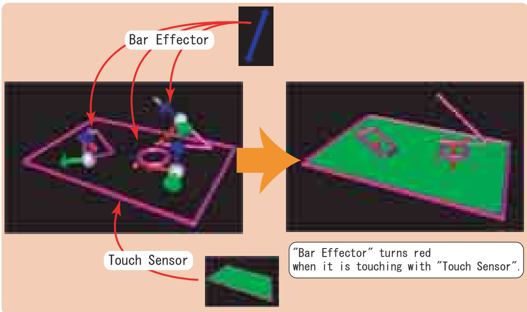

Figure 22. Model of object function using virtual sensors/effectors

(c) Associating output of object function model with activity event Human activity can be described using the output of the virtual sensors created in Step (b). In Fig. 23, red indicates that the cup touches the desk, and blue indicates that the cup does not. By creating a table describing the relationship between the output of the virtual sensors and the target events, the system can output symbolic information such as "put a cup on the desk" when the states of the virtual sensors change.

(d) Detecting human activity events in real time When the software inputs the position data of the ultrasonic tag, the software can detect the target events using the virtual sensors and the table defined in Steps (a) to (c), as shown in Fig. 24.

6. Conclusion

This paper described a system for robustly detecting daily human activity events in the handling of objects in

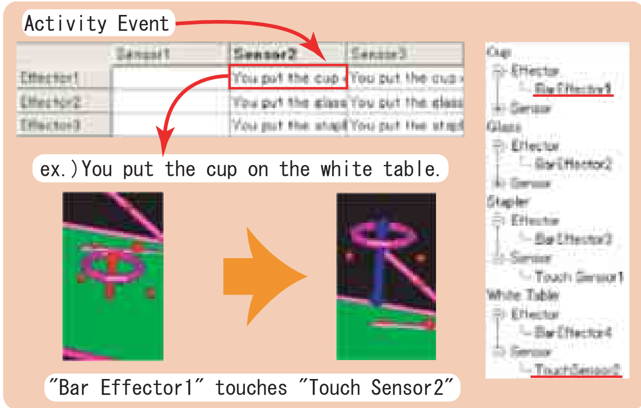

Figure 23. Association between output of virtual sensors and target activity event

the real world, with supporting calibration and registration tools to allow the system to be set up quickly. The system robustly measures the 3D position of objects and robustly detects the registered events in real time. Estimation of the 3D position with high accuracy, high resolution, and robustness to occlusion is performed using a RANSAC-based estimation method. The system was tested in an experimental room ($3.5 \times 3.5 \times 2.7$ m) fitted with 307 ultrasonic receivers embedded in the walls and ceiling, and it was demonstrated that it is possible to improve the accuracy, resolution, and robustness to occlusion by increasing the number of ultrasonic receivers and by adopting a robust estimator such as RANSAC to estimate the 3D position based on redundant distance data. The resolution of the system is 15 mm horizontally and 5 mm vertically using sensors in the ceiling, and the total spatially varying position error is 20–80 mm. It was also confirmed that the system can track moving objects in real time, regardless of obstructions.

The quick calibration method involves the use of a calibration device with 3 or 4 ultrasonic transmitters. By arbitrarily placing the device at multiple positions and measuring distance data in local coordinates, the positions of the receivers can be calculated. The experimental results showed that the positions of 80 receivers could be calculated using 4 transmitters with a positioning error of only 103 mm.

The quick method for registering target human activity events in the handling of objects involves the use of a stereoscopic camera fitted with ultrasonic tags in combination with interactive software. The effectiveness of the function was confirmed by application of the registration procedure to examples such as "put a cup on the desk". Using simplified 3D shape models and event descriptions, users can easily input new events using simple mouse operations.

Further development of the system will include refine-

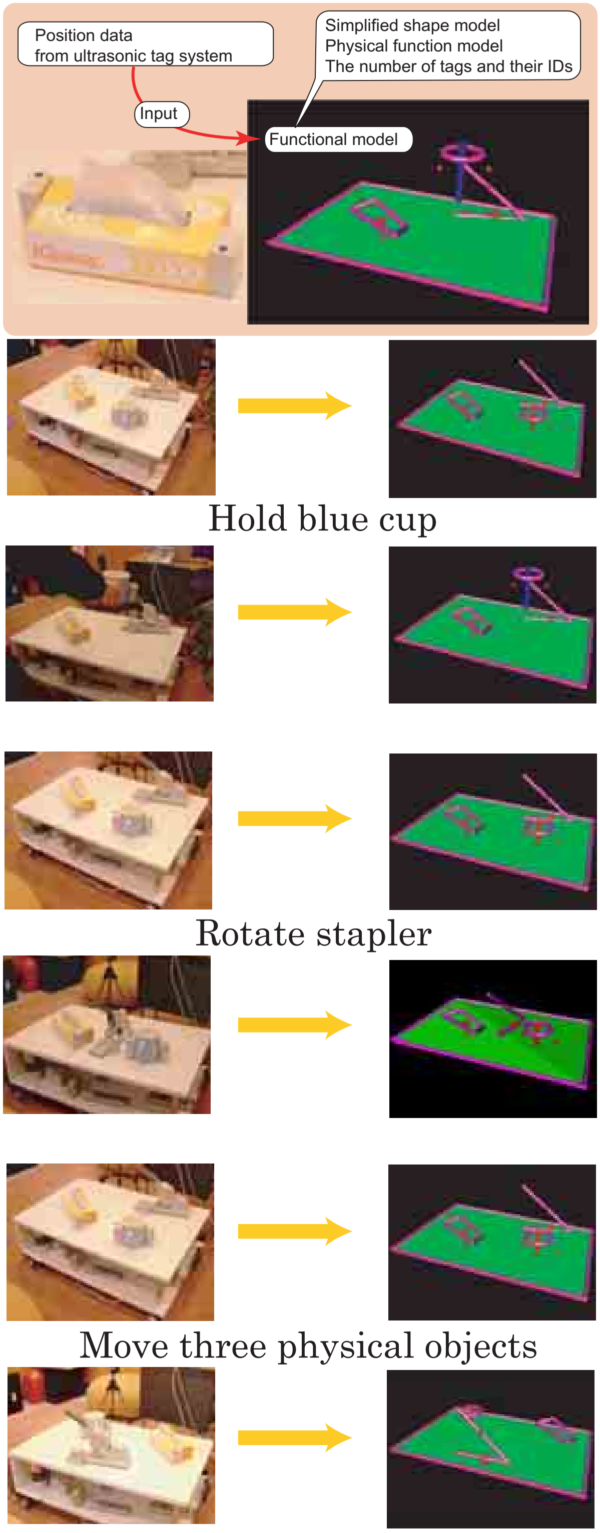

Figure 24. Recognition of human activity in real time using the function model

ment of the method for measuring the 3D position with higher accuracy and resolution, miniaturization of the ultrasonic transmitters, development of a systematic method for defining and recognizing human activities based on the tagging data and data from other sensor systems, and development of new applications based on human activity data.

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