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Measurement and Estimation of Indoor Human Behavior of Everyday Life Based on Floor Sensing with Minimal Invasion of Privacy

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Abstract— **This paper describes a method of measurement and estimation of human behaviors in a room together with the layout of objects on the floor. The information obtained by the method is essential for a service robot working in a human daily life environment. The method uses only one laser range finder (LRF) installed in the room and a strip of mirror attached to a side wall close to a floor. The area of sensing is limited to a plane parallel to and just a few centimeters above the floor, thus covering the whole room with minimal invasion of privacy of a resident while reducing occlusion. Processing both distance and reflectance acquired by the LRF from the surface of the existing objects allows us to exclude immediately distinguishable clusters and to focus on the analysis of remaining clusters. The human behavior models that we propose are effectively used to estimate human behavior based on the limited LRF data. Our experimental results validate the effectiveness of the proposed method.**

I. INTRODUCTION

Daily life assistance is one of the most important applications of service robots in the near future. A service robot must have a function for recognizing its surroundings. However, it is very difficult to recognize an environment of human daily life since it is a dynamically changing real space: there exist human beings walking and working around while the space is cluttered with furniture and everyday objects. It is quite difficult to recognize its surroundings for a robot by only using sensors mounted on its limited body. An alternative and promising approach would be to construct an informationally structured environment embedded with distributed sensors combined with a data-base of the environment[1], [2]. In this paper, we propose a method to measure and estimate human behavior and location of various everyday objects in a room, a private indoor space, while protecting privacy of residents.

An ordinary room for everyday life is equipped with furniture. Also everyday objects of various size and shape exist there. The layout of small furniture like a chair often changes and small objects are moved due to the daily human activity. It is very difficult to directly measure all the human behavior and displacement of objects by using sensors. Vision sensors suffer from illumination change and occlusion. In addition, deployment of multiple cameras is needed to complement the incompatibility of range of view and the resolution of sensing. However, embedding so many cameras in our daily life environment so that almost all the space is within the visible space would be expensive and tedious due to initial setups and later maintenance of wiring, fixture, calibration, lighting control and so on. Furthermore it is not acceptable for residents because of possible invasion of their privacy.

This paper proposes a novel method of measurement and estimation of daily human behavior in a room together with the layout of objects on the floor. The method uses only one LRF fixed on the floor very close to the wall, therefore the sensor implementation is very simple and low cost. Since the range of view is limited to a scanning plane parallel to and a little above the floor by a couple of centimeters, the system causes minimal invasion of privacy while enabling acquisition of position data of human feet together with objects on the floor including small everyday objects. However, it is difficult to directly recognize the situation of surroundings since the available sensor data is limited. To overcome the difficulties, we introduce the following ideas.

1) *Reduction of occlusion by using LRF and a mirror*

The scanning plane of the LRF is carefully selected to be parallel and just a few centimeters above the floor so that there exist relatively few objects that cross the plane in our western style environment which contains a bed, chairs, tables and so on. This means that the sensing plane is less influenced by occlusion. In addition, a strip of mirror is attached to the side wall of the room so that the reflected laser rescans the floor. Thus the floor is scanned by the laser projected from two different positions. Therefore the furniture having legs with small cross section will not cause severe occlusion. In the case of the furniture having large support on the floor, we can lift it using small pillars to create space below for the scanned laser to pass through thus reducing occlusion.

2) *Distance value and reflectance value of objects*

The LRF provides both distance value and reflectance value when the laser beam is projected on the object surface. The reflectance value is a function of distance, angle of incidence of the laser to the surface, and optical

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property of the surface of the object. Objects can be distinguished by this normalized reflectance values if the difference is sufficiently large above the noise level. However, some objects have similar reflectance value. To expand the normalized reflectance value, a retroreflective tape is attached to the surface of the object of interest. The retroreflective material has a transparent surface in which micro glass balls are embedded so that the incident light is reflected back to the same direction. So it gives very high reflection and it is often used, for example, for traffic symbol panels. Attaching the retroreflective tape on the supporting part of stable furniture and mobile objects like wheeled robots makes them distinguishable by its reflection value. Only a small tape is enough for the previous object, since their vertical pose with respect to the floor is always kept. Furthermore, we have developed a method for identifying the pose of objects by attaching a tag coded by reflection value. This method has been successfully applied to pose measurement of a cylindrical robot which has no geometrical features useful for pose identification.

3) Human behavior model related to the usage of furniture for daily life

Human behavior in a room can be classified into four modes: walking, stopping, sitting down on a chair, and resting on a couch or bed. Human feet move differently depending on each mode. The floor sensing by LRF will lose sight of feet when the human is resting on a bed, however, walking feet can be observed approaching to and leaving from the bed before and after the rest. So we can establish models of human behavior corresponding to each mode in terms of how human feet are observed by the floor sensing system. Then the human behavior can be measured and estimated from sensor data based on these models.

II. RELATED WORK

LRF has been widely used to measure human motion[3], [4], [5]. In most of the previous works, the laser scanning plane is set to be horizontal at the height of the waist of an adult. However, this configuration has some disadvantages: the position measurement is influenced by the motion of arms and hands; small children cannot be measured; and tall tables and chairs located at the central area of the room may cause occlusion. Therefore, instantaneous measurement may be less accurate and less reliable, even though the long term trend of motion is available. Pedestrian tracking is reported in [6] by setting the scanning plane at the height of human leg. Though it has successfully tracked pedestrians at the railway station in Tokyo, it cannot distinguish other objects existing within the measurement area.

Elastic Pressure sensor has been used to measure human foot print [7], [8]. The position and the direction of the human foot can be measured if the resolution of the pressure sensor is 1cm or less. However such sensor device itself is expensive. Furthermore covering all the surface of the room is very expensive including wiring and later maintenance. Moreover the position measurement of light weight objects

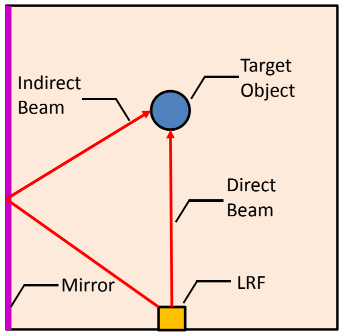


Fig. 1. Top view of floor sensing system using LRF and mirror

is difficult, although such objects made of tissue or paper exist everywhere in our daily environment.

Using cameras to track everyday objects in a room is reported in [9]. Measurements are influenced by change of illumination and occlusion. Furthermore it may not be desirable due to possible invasion of privacy. Everyday objects can be tracked once RFID or ultrasonic tags are attached to them [10], [11]. However active scanning of large directional antennas is required for tracking RFID tags. This is time consuming and resolution is rather low. In addition, the ultrasonic tag is rather large and expensive to be used on numerous everyday objects.

In our daily life, we often leave or drop everyday objects on the floor. Also, various objects, such as persons, robots, furniture and movable furniture may exist on the floor. Therefore, detection and position measurement of these objects on the floor is an important issue in the informationally structured environment.

III. INDOOR FLOOR SENSING FOR HUMAN FEET AND OBJECTS

A. Floor Sensing by a Laser Range Finder with a strip of Mirror on the Wall

We installed a LRF on a floor at one end of a room next to a wall so that the scanning plane is parallel to the floor at a height about 25mm above the floor. A strip of mirror is attached to a side wall to reflect the laser beam from the LRF. The measureable area is covered by the direct beams from the LRF and/or the indirect beams reflected by the mirror (Fig.1).

If no object is placed on the floor, the LRF measures the distance to the opposite wall. If an object is placed on the floor, the LRF measures the distance to the object. Even a small object is detected if it has a height of more than 25mm.

However, the LRF may not obtain any distance data due to the reflection property of the object. In this case, our system still obtains the distance value thanks to the combination of the LRF and the mirror as follows.

1) Object That Reflects Laser Beam: If an object reflects a sufficient laser beam, the LRF obtains the distance not to the wall but to the object. Then the system detects the existence of the object from this difference, and calculates the position

using the distance and the angle of the laser beam. Moreover, two types of the measurements can be obtained. One results is obtained using the direct laser beam from the object, and the other is obtained from the indirect laser beam via the mirror (Fig.1).

2) Object That Diffuses Laser Beam: If the placed object does not reflect the sufficient laser beam, e.g. a transparent plastic bottle, the LRF is unable to obtain any distance data. This implies that some object is placed somewhere on the line from the LRF to the wall. Also if the LRF fails to obtain indirect measurement, then some object is placed on the line from the LRF to the wall via the mirror. By integrating these two pieces of information, we can calculate the position of the object as the intersection of the two lines (Fig.1).

B. Laser Reflection Intensity of Everyday Objects

The LRF(Hokuyo URG-30LX) measures not only distance values but also intensity values of laser reflections. We use geometric information and material information to classify persons, robots, furniture, and everyday objects made of wood, paper, plastic and rubber in daily environment (Fig.2). Figures 3 show the reflection feature for each object material. The reflection intensity varies depending not only on the optical property of objects but also on the distance and angle of incidence of the laser beam (Fig.3). We obtain the intrinsic intensity of reflectance by normalizing the obtained reflection value with respect to distance and angle of incidence.

In our model, we exclude the first 800mm from our measurement due to the strong discontinuity of reflection intensity curve with other part (Fig.3). Then, we obtained Eq.(1) by curve fitting using experimental data. Finally, the approximate intrinsic intensity (2) was obtained using Eq. (1) with measured intensity, r and α from LRF.

$$Intensity = K_d I_q \frac{\cos(\alpha)^{0.196}}{r^{0.287}} \tag{1}$$

$$IntrinsicIntensity = Intensity \frac{r^{0.287}}{\cos(\alpha)^{0.196}} \tag{2}$$

K_d : *diffuse reflection coefficient*
I_q : *the power of the light source*
α : *angle of incidence on the surface*
r : *distance from the light source*

Next, we evaluate the effect of the normalization using Eq. (1), (2). A piece of wood, a red bucket, a green plastic bucket, and a cardboard box were placed at 2-3 m in front of the LRF (Fig.4). The reflection intensity data from the surface of each object is shown in Fig.5. Moreover the normalized reflection intensity of each object is obtained in Fig.6. If there is a difference in the reflection intensity among the objects, then they can be classified immediately.

C. Expanding Reflection by Attaching the Retro-reflective Material

If there is no enough difference in the reflection value of each object, we cannot classify the object using only

Fig. 2. Objects in daily environment

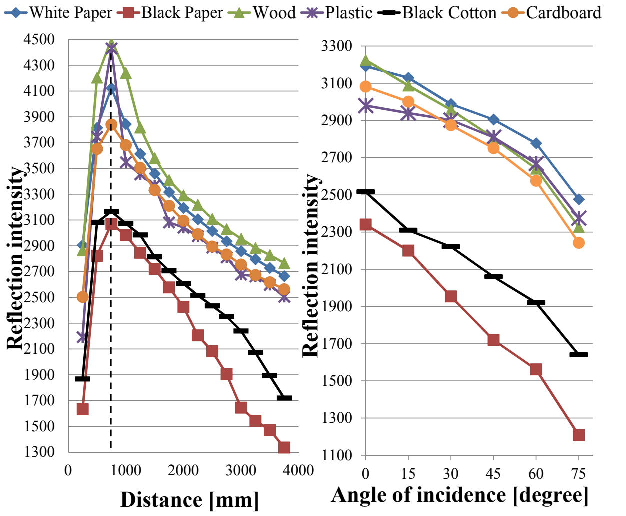


Fig. 3. Experiment results of reflection intensity vs. distance and angle of incidence

Fig. 4. Experiment setups

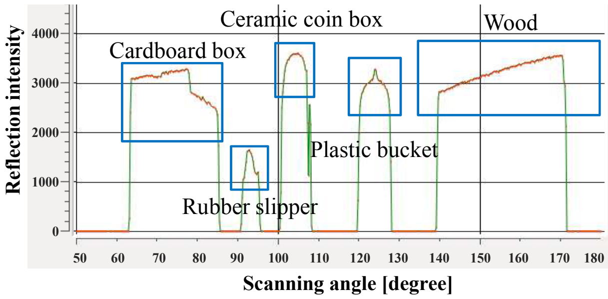


Fig. 5. Reflection intensity value of each object

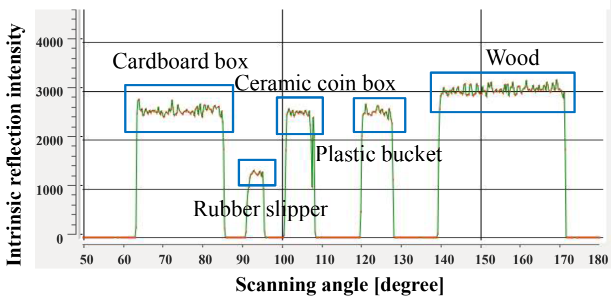


Fig. 6. Normalized reflection intensity value of each object

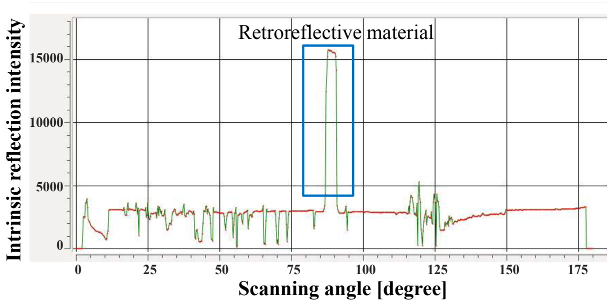


Fig. 7. Reflection Intensity value of retroreflective material

reflection intensity. To solve this problem, we attached a tape made of retroreflective material to the object. Thus, the difference of the reflection features becomes large (Fig.7). Using this simple method, we will be able to classify objects based on the distance and the reflection intensity.

IV. OBJECT DETECTION INSIDE INDOOR ENVIRONMENT

A. Measuring Human Activity and Object Layout by the Floor Sensing System

The main goal of our system is to measure the trajectory of human walking and mobile robots. Moreover we obtain the layout of furniture such as tables, chairs and a mobile dining wagon. And finally we obtain the location of everyday objects on the floor. Clusters of points are obtained by the LRF. By analyzing a sequence of these clusters, motion tracking of objects is achieved.

The measurable data correspond only to partial profile of object from the LRF. Moreover some objects may be invisible due to the occlusion by other objects. In addition, it may be often difficult to separate the multiple clusters when they are closely located. This happens for example when a person approaches a table or sits down on a chair. Therefore, it is not easy to accurately classify and track objects in real time.

To solve these problems, we use the reflection intensity and position information obtained from the target surface. Although it is not possible to classify all objects by additionally using reflection values, it would be easier to classify unknown clusters if we can eliminate easily classifiable objects by reflectance.

B. Improvement of Reflectance Detection by Attaching Retroreflective Materials

Our daily life environments (Fig.1) contains some furniture that can be moved by a person like for example, a chair and a dining cart (Fig.8). We attach the retroreflective material on the surface of legs of the chair and wheels of the dining cart where the laser scans. Furthermore, we attach semi-transparent sheet over the retroreflective material to control the reflection intensity. As a result, they will be easily classified only by the reflection intensity as shown in Fig.9.

Figure 8 shows how the retroreflective material is attached to the legs of movable furniture. Since the tags are small, they

Fig. 8. Position of retroreflective material

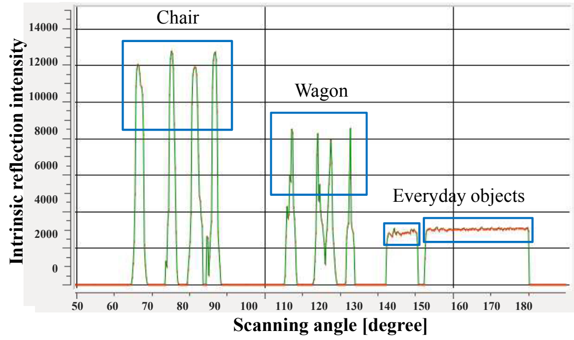


Fig. 9. Distinctly different intensity compared to the other objects

will not affect general appearance of these objects. This is good for keeping our daily environment as it used to be even if service robots are working around.

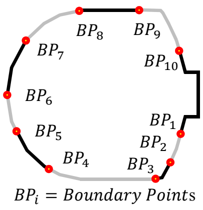
C. Measurement of Robot Pose by Coded Reflection

It is not possible to determine the orientation of object based on the distance value obtained by LRF if the horizontal cross-section of the object is rotationally symmetric with respect to the vertical axis of rotation. However, there are certain objects that have circular cross-section shape. A cylindrical mobile robot is a typical example. We developed a method to measure the orientation in such cases.

The idea is to attach distinguishable optical features around the robot base. An optical feature is in our case a transition between reflective and not reflective material. This transitions are indicated in Fig.10a as boundary points BPs. Geometric distance between optical features is designed so that they are distinguished from each other around the robot base as shown in Figs. 10a, 10b and 10c.

Once the robot base is scanned by the LRF, visible optical features are detected and identified (Fig.10d), and then are matched with the robot base model (Fig.10e). The complete pose of the robot is computed based on the position of identified features.

We have wrapped a strip of reflection encoded tape around the body of a Roomba robot and evaluated accuracy of the pose measurement. The robot was located at 9 different positions as shown in Fig.11. At the right center position, the robot took 8 different orientations. We have measured 100 times for each pose and obtained mean errors of 5.6mm along x-axis, 3.5mm along y-axis, and 3.4degrees about vertical axis. The variance was 18.9mm, 16.9mm, 9.5degrees respectively.

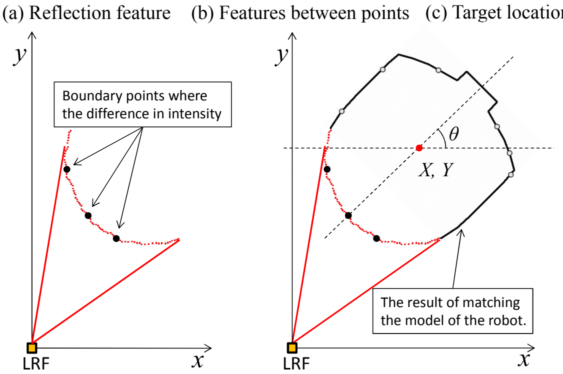


(a) Reflection feature

Line	Distance	Intensity
$\overline{BP_1 BP_2}$	98mm	High
$\overline{BP_2 BP_3}$	87mm	Low
$\overline{BP_3 BP_4}$	157mm	High
$\overline{BP_4 BP_5}$	141mm	Low
$\overline{BP_5 BP_6}$	194mm	High
$\overline{BP_6 BP_7}$	195mm	Low
$\overline{BP_7 BP_8}$	243mm	High
$\overline{BP_8 BP_9}$	223mm	Low
$\overline{BP_9 BP_{10}}$	344mm	High
$\overline{BP_{10} BP_1}$	325mm	Low

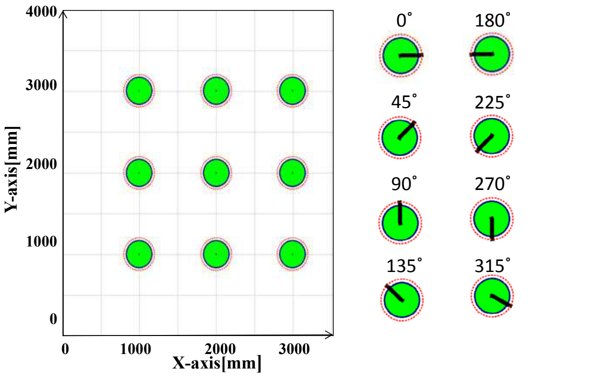
(b) Features between points


(c) Target location



(d) Laser scan data (e) Result of matching

Fig. 10. Eaxample for measurement of robot position



(a) Evaluation of position error (x, y axis) (b) Evaluation of direction error (θ)

Fig. 11. Evaluation of pose error

V. MODEL BASED ESTIMATION OF HUMAN BEHAVIOR

A. Human Behavior Model

It is very difficult to correctly find human feet based on the shape of cluster and reflectance value in the single scan data obtained from LRF when the resident is walking in the room populated with furniture and everyday objects on the floor. Therefore we use time series of consecutive scans to find human feet and to recognize human behaviors.

Human behavior in a room can be classified into four modes: walk, stop and standing still, sitting down on a chair, and resting on a couch or bed. Human feet move differently depending on each mode. The floor sensing by LRF will lose sight of feet when the human is resting on a bed, however, walking feet can be observed when approaching to and leaving from the bed before and after the rest. So we establish models of human behaviors corresponding to each mode in terms of how the human feet are observed by the floor sensing system, and then based on these models the human behavior is measured and estimated from sensor data.

1) Ordinary walk

The left foot and the right foot of a walker repeat moving in air and landing on the floor alternately. In the floor sensing data, appearance and disappearance of clusters repeat in a constant walk cycle. The disappeared cluster appears within the stride after a period of a walking cycle. This appearance may be influenced by self-occlusion by another foot and/or occlusion by objects on the floor.

2) Standing still

A resident stands still while he is picking up objects on the floor, taking out objects from a cabinet, or putting objects into a cabinet. Transition from ordinary walking occurs and clusters of two feet typically approach each other and stop.

3) Sitting down on a chair

While sitting, clusters of feet irregularly approach, disappear, appear, and stop near the chair. Mutual occlusion among human feet and chair legs occurs. Transition between this mode and ordinary walking mode occurs.

4) Staying on the bed

After approaching the bed, the clusters of feet disappear. When leaving the bed, the clusters appear again and transition to ordinary walking mode occurs.

B. Unified Estimation of Human Behavior based on different Human Behavior Models

The human motion is composed of a series of different mode of behaviors. Possible transition among different mode of behaviors is analyzed to establish a mode transition diagram (Fig.12). Then based on this transition diagram, human behavior is estimated as shown in Fig.13.

Estimation modules of human behavior are implemented corresponding to each human behavior models. These modules work on the input LRF data independently and output the estimation result in parallel in every 1s. Then the behavior is uniquely estimated according to the mode transition diagram (Fig.13).

VI. EXPERIMENTAL RESULTS

We have performed experiments for estimating human behaviors in our everyday life environment shown in Fig.14. Roomba is waiting for command. A bed is set at a corner of the room. A desk and a bookshelf are located along a wall. A table and a chair are positioned at the center area. Since the robot and the chair are equipped with retroreflective tape, they are immediately identified based on the reflectance intensity value by the LRF sensing system. Distance data from other pieces of furniture is treated as background data because they are not movable.

The scenario of the experiment is as follows:
1) A resident enters the room in ordinary walk mode.
2) He comes to a book shelf and stands still to pick up one book.

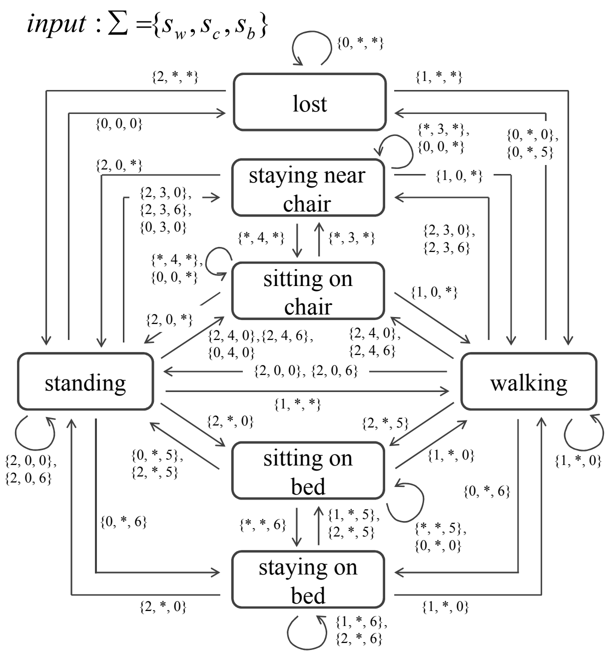


Fig. 12. Mode transition diagram

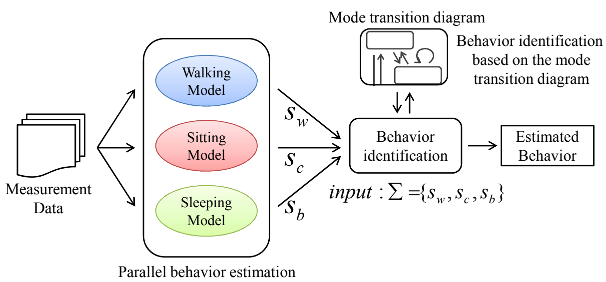


Fig. 13. Flow of human behavior estimation

TABLE I

ASSIGNMENT OF NUMBERS TO BEHAVIOR

Number	Behavoir
0	Lost
1	Walking
2	Standing
3	Staying near chair
4	Sitting on chair
5	Sitting on bed
6	Staying on bed

3) Then he approaches the table.
4) He sits on the chair for reading the book.
5) He stands up and approaches the book shelf to return it.
6) Then he walks out the room.
7) He enters the room again, approaches the bed.
8) He sits on the bed.
9) He lay down on the bed.
10) Finally he gets up and walks out of the room.

The original data obtained by the LRF is cluttered with many data points as shown in Fig.15a. The clusters belonging to the robot and the chair are recognized based on the reflection values as shown in Fig.15b, then the clusters of

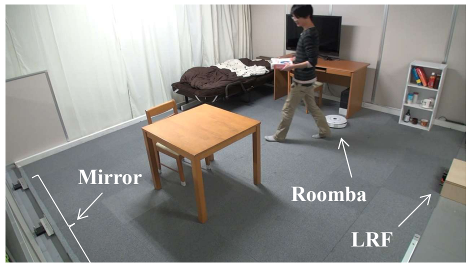
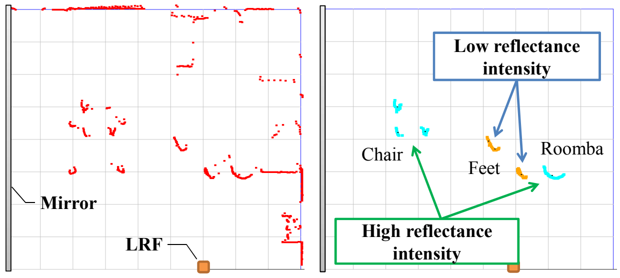


Fig. 14. Everyday life environment



(a) Original data points (b) Recognition of feet clusters

Fig. 15. Original data by LRF

human feet are obtained in the remaining clusters.

The trajectory of the human feet was obtained as shown in Fig.16, corresponding well to the behavior scenario of the experiment. The result of behavior estimation is shown in Fig.17, where the estimated behavior is arranged along the vertical axis and the time is shown in second in the horizontal axis. Fig.17a shows outputs of each estimation module of behavior model. The outputs are unified based on the mode transition diagram as shown in Fig.17b.

The module of walking/standing-still model estimates either walking or standing-still, and outputs corresponding number, 1 or 2 (See table I). The module outputs 0 meaning "lost" when the resident of the room is out, staying on the bed, or when the module fails identifying the behavior due to, for example, occlusion or noise.

The chair sitting module outputs 4 when the resident is reading a book on the chair, and outputs 3 meaning that he is staying near the chair before and after the sitting mode (① in Fig.17a). This is because the foot clusters are measured near the chair while he is moving it to sit on and to leave from. The mode of staying near the chair is also identified for a short period when he walks near the chair while moving toward the door after staying on the bed (② in Fig.17a). In this short period, the walking/staying module outputs 1 estimating "walking" simultaneously and independently. Then unified estimate is made to be "walking" based on the mode transition diagram (②' in Fig.17b). The part ③ in Fig.17b corresponds to "leaving out of the room" in the scenario. This part is correctly estimated because the cluster being tracked has disappeared near the door and then appeared later again. The dashed blue line in Fig.17b shows the grand truth obtained by human observation of the video image of the experiment. Estimated sequence of human behavior coincides mostly with the truth.

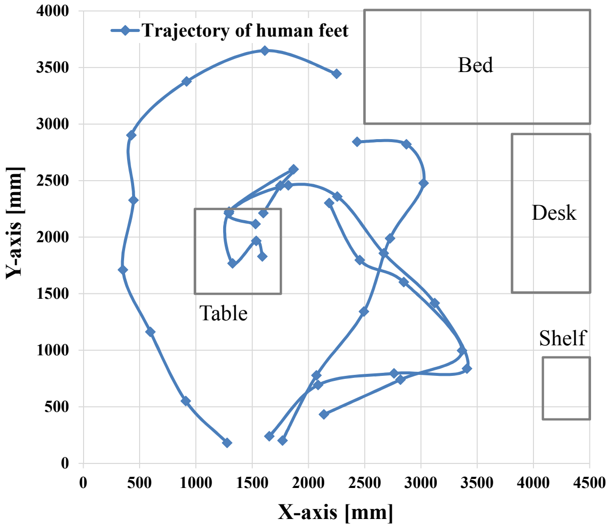


Fig. 16. Trajectory of human feet

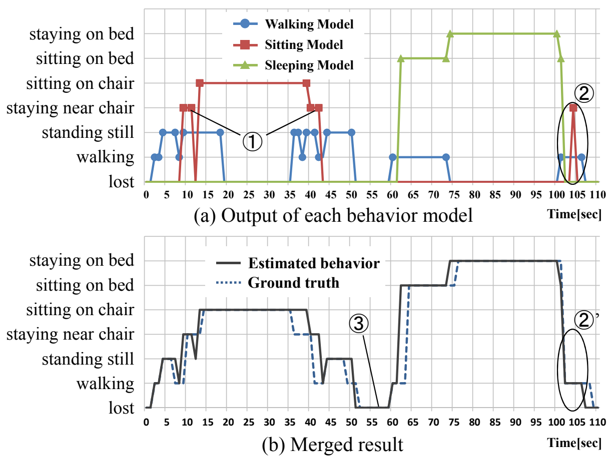


Fig. 17. Estimation result

Table II shows the evaluation of resulted estimate of experiment with 10 subjects.

VII. CONCLUSION

A method of measurement and estimation of both human behavior in a room and layout of objects on the floor has been proposed. The ultimate goal of this work is to provide information of surroundings to a service robot working in a dynamically changing human daily life environment. The proposed sensing system design enables the acquisition of the above mentioned data by using only one laser range finder (LRF) in a room thus achieving minimal invasion of privacy of a resident. The system simultaneously utilizes distance measurement data and reflectance measurement data obtained by LRF from the surface of objects. Human behavior models and the model based estimation have been implemented and the experiments validate effectiveness of our approach.

Future work would include a more complete set of human behavior models and robust estimation of the human behaviors.

TABLE II

RECALL AND PRECISION RESULT

Person	Recall	Precision
1	93.3%	93.3%
2	93.3%	87.5%
3	86.7%	81.3%
4	100%	93.8%
5	93.3%	87.5%
6	86.7%	86.7%
7	100%	88.2%
8	93.3%	93.3%
9	73.3%	70.6%
10	93.3%	87.5%
Average	91.3%	87.0%

VIII. ACKNOWLEDGEMENTS

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