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Fuzzy Inference Based Non-Daily Behavior Pattern Detection for Elderly People Monitoring System

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Abstract— **This paper describes an abnormal behavior detection system based on an omni-directional vision sensor as one of the important elements in realizing "Sensing and Robotic Support Room" for elderly people. Such support rooms are expected to be further developed in the future with the high performance to automatically recognize elderly people's actions and behavior patterns and detect the unusual patterns using some sensors and to support their daily motions using some robotic manipulator control systems. The proposed monitoring system using an omni-directional vision sensor automatically learns the daily behavior patterns and detects the unusual behavior patterns and actions using fuzzy inference approach. The fuzzy rules are constructed using image feature values such as the area and center-of gravity values extracted from the captured image sequence and their patterns appearance frequency. Unusual behavior patterns can be automatically detected based on the possibility distribution inference method. Some experiments based on the investigation of elderly people's typical daily behavior patterns show the effectiveness of the proposed system.**

I. INTRODUCTION

The number of elderly people is recently increasing and this problem will be more serious in the near future. Especially the number of elderly people who are living alone is increasing, therefore, some monitoring system keeping an eye on such elderly people has to be developed in order to put them at ease and to surely detect their unusual situation and behavior. Some researchers have developed such monitoring system using many sensors such as infrared sensors, however, more inexpensive and convenient monitoring systems are required to be widely used in the practical society.

This study aims at realizing a vision sensor based behavior monitoring system only using an omni-directional camera to automatically detect the unusual behavior patterns of elderly people. If the unusual behavior pattern is detected, the system immediately reports to the family and medical institution. In addition, such monitoring system can be one of the important elements in "Sensing and Robotic Support Room" [1][2], as shown in Fig.1, to measure and recognize elderly people's actions and behavior patterns and support them using some robot manipulators.

This study applies an omni-directional vision sensor and proposes a non-daily behavior pattern detection system based on fuzzy inference. If he/she acts differently from usual behavior patterns, the proposed monitoring system automatically detects it based on the learning results of usual behavior patterns. In addition, some experiments will be conducted based on the detail investigation of elderly people's typical behavior pattern statistics.

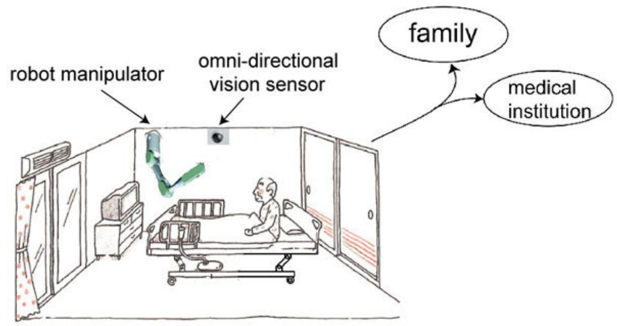

Fig. 1. Behavior monitoring system in "Sensing and Robotic Support Room".

II. BEHAVIOR MONITORING SYSTEM FOR ELDERLY PEOPLE

A. Investigation of elderly people's typical daily behavior patterns

At first the practical detail data of elderly people's typical daily behavior patterns will be investigated. Table I shows the elderly people's average behavior time at week investigated by Statistics Bureau in Japanese Ministry of Internal Affairs and Communications in 2006. These typical behavior patterns and the proportion will be applied to the experiments in this paper.

behavior	average time (min./week)
Sleep	523
Watching TV, etc	250
Other activities	159
Rest and relaxation	124
Housework	122
Meals	120
Personal care	87
Hobbies and amusements	49

TABLE I
ELDERLY PEOPLE'S TYPICAL BEHAVIOR PATTERNS.

B. Human action and behavior analysis

Some algorithms for the human action recognition from image sequences have been proposed, for example, DP matching [3], HMM [4], Temporal Templates [5] and eigenspace representation [6]. However, the purpose of this study is not to recognize and classify the various human

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actions and behavior patterns but to detect the unusual behavior patterns by comparing with the learning patterns.

Some researchers have tried the unusual event detection including human behavior using general vision sensors by hidden Markov model(HMM), Bayesian Network and optical flow [7][8][9][10]. In addition, several types of sensors connecting by sensor network are also applied to the abnormal human activity detection [11].

The author have proposed the CCD camera based monitoring system for elderly people using Self-Organizing Map and eigenspace representation[12]. This study will develop the omni-directional vision sensor based monitoring system with the image feature analysis because omni-directional sensors can look over the whole room and understand the human position and posture well [13].

As previous work using omni-directional vision sensor, the author proposed an unusual behavior detection system based on Bayesian Network approach and could successfully detect some unusual behavior patterns such as falling to the floor and walking around at midnight [14]. However, the proposed system using Bayesian Network necessarily discretized the image feature values such as the area, center-of-gravity and behavior time in order to assign some labels to the network nodes. This discretization brought the discontinuous inference with low accuracy around the discretizing borders. Therefore, this study will treat them as continuous values using fuzzy variable representation.

C. Experimental monitoring system

Fig.2 shows the omni-directional vision sensor used in this study and it is placed in the center of the room. The human position and posture, standing, sitting or lying, can be clearly recognized though the obtained images are little distorted.

The experimental monitoring room used in this study is constructed mainly from white color in order to make the human region extraction easy. Fig.3 shows an example of the captured images by the omni-directional vision sensor.

Fig. 2. Omni-directional camera.

Fig. 3. Captured image.

III. NON-DAILY BEHAVIOR PATTERN DETECTION BASED ON FUZZY INFERENCE

A. Pre-processing for captured image

As the first pre-processing for the captured images, the human region is extracted through the binarization by the simple subtraction from the background image. In addition, the noise removal is also conducted by Median Filter. Fig.4(a)(b) show examples of these processing results.

(a) original image

(b) binarized image

Fig. 4. Pre-processing results.

B. Image feature extraction

After the pre-processing, some image feature values for the human region have to be extracted in order to analyze the human actions and behavior patterns. This study focuses on the following image feature values.

1) Area: The area value N of the human region is easily calculated by counting the pixel in the human region. This value includes the important information to detect the unusual behavior patterns, for example, the human body's posture and the distance from the camera.

2) Center of gravity: The coordinates of the center of gravity pixel $\boldsymbol{\mu}= (X_c, Y_c)$ is calculated because this value includes the important information such as the human's position.

3) Covariance matrix: Covariance matrix is calculated as shown in the following equation.

$$\boldsymbol{Q} = \begin{pmatrix} C_{XX} & C_{XY} \\ C_{YX} & C_{YY} \end{pmatrix} = \frac{1}{N-1} \sum_{i=1}^{N} (\boldsymbol{x}_i - \boldsymbol{\mu})(\boldsymbol{x}_i - \boldsymbol{\mu})^T \quad (1)$$

The coordinate $\boldsymbol{x}_i$ shows the pixel in the human region. These values, C_{XX}, C_{XY}, C_{YY}, include the important information such as the human body's posture. This study applies only C_{XX}, C_{YY}.

4) Behavior time: The behavior time t is not an image feature values but is very important for the elderly people's behavior analysis. For example, the behavior patterns of sleeping long time in the daytime and walking around at midnight should be judged as the abnormal patterns. Therefore this information will be applied to the learning and abnormality detection system.

C. Fuzzy Variable Design

As mentioned above, this study treats the image feature values as continuous values by defining six fuzzy variables, $x_{AREA} = N$, $x_{COGX} = X_c$, $x_{COGY} = Y_c$, $x_{COVX} = C_{XX}$, $x_{COVY} = C_{YY}$, and $x_{TIME} = t$. Fig.5,6,7,8 show the triangular fuzzy variables and membership functions for the area x_{AREA}, center-of-gravity of x direction x_{COGX}, center-of-gravity of y direction x_{COGY}, covariance of x direction x_{COVX}, covariance of y direction x_{COVY} and time x_{TIME}. These six variables will be applied to the premise variables in the conditional sentence of fuzzy rules. The membership functions $A^k_{AREA}(x_{AREA})$, $A^k_{COGX}(x_{COGX})$, $A^k_{COGY}(x_{COGY})$, $A^k_{COVX}(x_{COVX})$, $A^k_{COVY}(x_{COVX})$ and $A^k_{TIME}(x_{TIME})$ are called premise parameters for kth rule R^k.

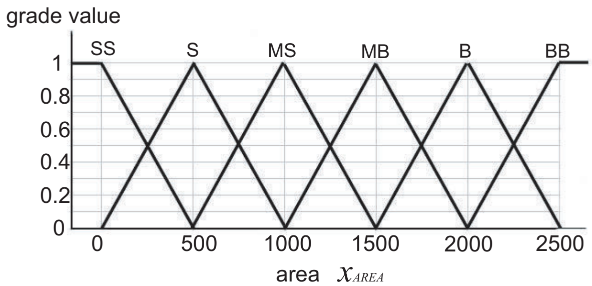
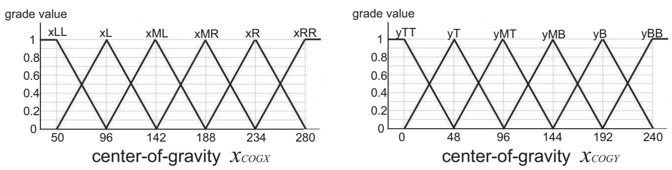


Fig. 5. Triangular fuzzy variable and membership function of area.



(a) x direction (b) y direction

Fig. 6. Triangular fuzzy variable and membership function of center-of-gravity.

The fuzzy membership function for area has six symbols, "SS"(Small-Small), "S"(Small), "MS"(Middle-Small), "MB"(Middle-Big), "B"(Big) and "BB"(Big-Big).

The fuzzy membership function for center-of-gravity of x direction x_{AREA} has six symbols, "xLL"(x-Left-Left), "xL"(x-Left), "xML"(x-Middle-Left), "xMR"(x-Middle-Right), "xR"(x-Right) and "xRR"(x-Right-Right).

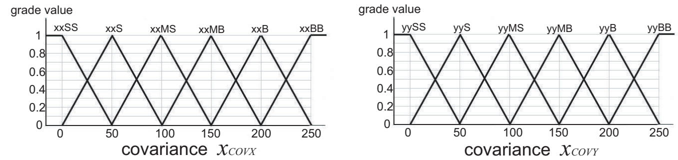
The fuzzy membership function for center-of-gravity of y direction x_{COGX} has six symbols, "yTT"(y-Top-Top), "yT"(y-Top), "yMT"(y-Middle-Top), "yMB"(y-Middle-Bottom), "yB"(y-Bottom) and "yBB"(y-Bottom-Bottom).

The fuzzy membership function for covariance of x direction x_{COVX} has six symbols, "xxSS"(xx-Small-Small), "xxS"(xx-Small), "xxMS"(xx-Middle-Small), "xxMB"(xx-Middle-Big), "xxB"(xx-Big) and "xxBB"(xx-Big-Big).

The fuzzy membership function for covariance of y direction x_{COVY} has six symbols, "yySS"(yy-Small-Small), "yyS"(yy-Small), "yyMS"(yy-Middle-Small), "yyMB"(yy-Middle-Big), "yyB"(yy-Big) and "yyBB"(yy-Big-Big).

The fuzzy membership function for time x_{TIME} has eight symbols, "LN"(Late-Night), "EM"(Early-Morning), "MM"(Morning), "NO"(Noon), "AN"(Afternoon), "EV"(Evening), "EN"(Early-Night) and "MN"(Midnight).

It is true that all these image feature values have the important information to judge the abnormality of the human actions and behavior patterns, but it is impossible to detect the abnormality by focusing on any individual image feature values independently. For example, even if both the area value and the center of gravity are similar to the learning data, it must be unusual when the combination of their values is different from the learning data. Therefore, the combination and correlation among these image feature values should be learned. This study learns such relationships as the fuzzy rules and regards some frequent patterns as



(a) x direction (b) y direction

Fig. 7. Triangular fuzzy variable and membership function of covariance.

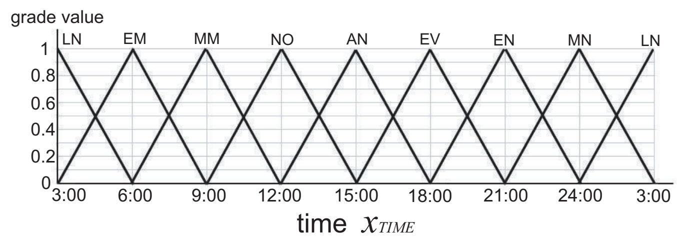


Fig. 8. Triangular fuzzy variable and membership function of time.

usual behavior patterns. In the stage of abnormality detection, the possibility distribution of input images will be inferred using "possibility distribution inference method" proposed by Nakamori [15].

D. Learning Algorithm of Daily Behavior pattern

The daily behavior pattern learning is conducted using all learning images by determining the full set of fuzzy rules including premise part and consequent part. Table II shows an example of the determined fuzzy rules.

	premise part						consequent part
rule	AREA	COGX	COGY	COVX	COVY	TIME	ANSWER
R^1	SS	xLL	yTT	xxSS	yySS	LN	N
R^2	S	xLL	yTT	xxSS	yySS	LN	N
R^3	MS	xLL	yTT	xxSS	yySS	LN	MN
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.

TABLE II
EXAMPLE OF THE DETERMINED FUZZY RULES.

The premise part shows the combination patterns of image feature and the consequent part necessarily shows the degree of abnormality. Then how to determine the consequent part is very important. This study assigns five patterns of answer in the consequent part, "N"(Normal), "MN"(Middle-Normal), "M"(Middle), "MA"(Middle-Abnormal) and "A"(Abnormal).

In this study, the consequent part will be determined based on the appearance frequency of the image feature pattern in the learning image sequence, that is, some image patterns which frequently appear in the learning image samples, for example, sleeping on the bed and having a meal, will be regarded as the normal patterns. Of course image patterns which rarely appear in the learning image samples should be regarded as the abnormal patterns. Therefore, in the learning stage, the number of image frames with the same feature pattern is counted for all combinations of the image feature pattern shown in the premise part.

In addition, this study also considers the neighboring similar patterns of the normal patterns which appears in the learning image samples because it's quite possible that a few image feature values change a little from the learning patterns, for example, the little difference of the body posture, sitting position and behavior time, and they should be flexibly judged as the nearly normal pattern.

In the triangular fuzzy membership function such as Fig.5, only two fuzzy symbols have non-zero values. For example, in Fig.5, when S=0.6 and SS=0.4, other symbols (MS, MB, B, BB) are zero. If the normal image patterns found in the learning image samples have two similar values, for example, S=0.51 and SS=0.49, then not only the pattern with S but also the pattern with SS should be considered in the consequent part's rule determination. In this study, if the second largest grade is larger than 0.45, such neighboring pattern is also flexibly judged as the nearly normal pattern. Let n be the number of such replacement of the image features.

Table III shows how to determine the consequent part rule based on the pattern appearance frequency (the counted number of image frames with the same feature pattern) and neighboring patterns (the number n of replaced image features). For example, if the number of image frames in the learning image samples is larger than 20 and the number of replaced features is zero, it is regarded as "N"(Normal). The larger the number of frames is, the lower the abnormality is, and the larger the value of n is, the higher the abnormality is.

	the number of frames			
	20∼	6∼20	1∼5	0
n=0	N	MN	M	A
1	MN	M	MA	A
2	M	MA	A	A
3	MA	A	A	A
4	A	A	A	A
5	A	A	A	A
6	A	A	A	A

TABLE III

HOW TO DETERMINE THE CONSEQUENT PART BASED ON PATTERN APPEARANCE FREQUENCY AND NEIGHBORING PATTERNS.

Fig.9 shows the proposed learning processing procedures based on fuzzy inference described in this section.

E. Non-Daily Behavior Pattern Detection Algorithm

In the stage of abnormality detection, each input image (behavior pattern) is judged, "normal" or "abnormal". First, the same pre-processing and fuzzy variable representation as the learning stage are conducted.

In the abnormality detection, the abnormality should be quantitatively evaluated in order to judge the input image (behavior pattern) normal or abnormal. This study insists that the quantitative evaluation of the abnormality can be realized by estimating the appearance possibility of the input image pattern. Then the possibility distribution inference [15] is applied to estimate the possibility that such image pattern appears.

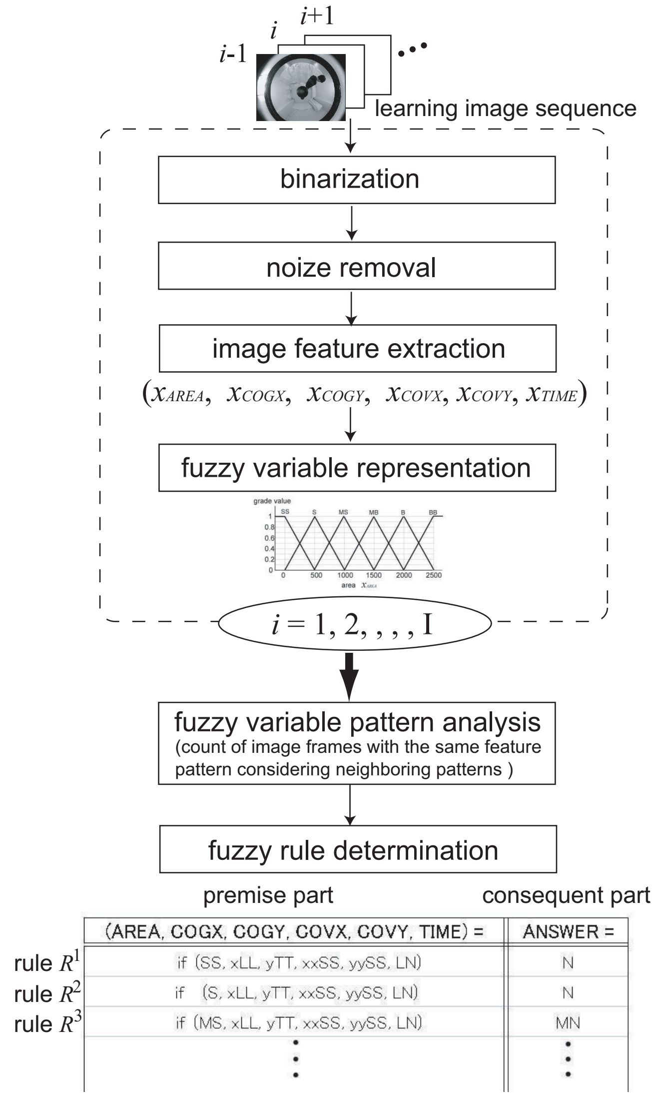


Fig. 9. Learning processing procedures based on fuzzy variables and rules.

The possibility distribution value y can be inferred by the following equations.

$$w^k = \prod_j A_j^k(x_j) \tag{2}$$

$$y = \frac{\sum_{k=1}^K w^k \mu^k}{\sum_{k=1}^K w^k} \tag{3}$$

The symbol $A_j^k(x_j)$ means the membership function such as $A^k_{AREA}(x_{AREA})$ and $A^k_{COGX}(x_{COGX})$. The symbol K is the number of fuzzy rules. The symbol w^k is the degree of confidence of rule R^k and is given by the product of membership grades corresponding to input values of all premise variables. The symbol μ^k is the output value from the rule R^k and the output y is given by the weighted average of all rule's output.

Table IV shows the output value μ^k from the rule R^k for five fuzzy symbols in consequent part. If the rule in consequent part is "N" (normal), this inference outputs $\mu^k = 1$. If the rule in consequent part is "A" (abnormal), this inference outputs $\mu^k = 0$. Therefore, the input image pattern can be judged normal when the inference output value y $(0 \leq y \leq 1)$ is large. In the practical system, it can be judged normal if $y > y_{th}$ using some threshold y_{th}, for example, $y_{th} = 0.7$.

symbol	meaning	value of μ^k
N	normal	1
MN	middle normal	0.75
M	middle	0.5
MA	middle abnormal	0.25
A	abnormal	0

TABLE IV

FUZZY SYMBOLS IN CONSEQUENT PART AND OUTPUT VALUE μ^k.

Fig.10 shows the proposed abnormality detection procedures based on fuzzy inference described in this section.

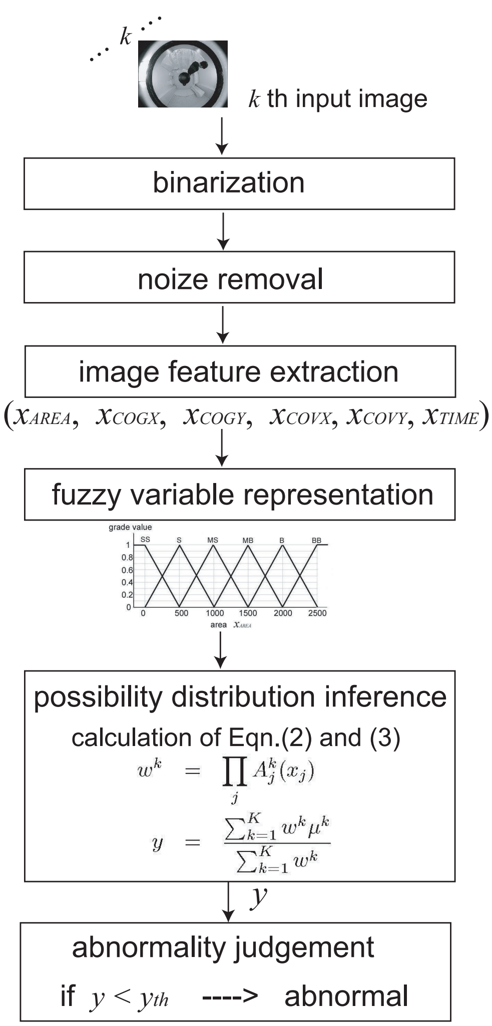


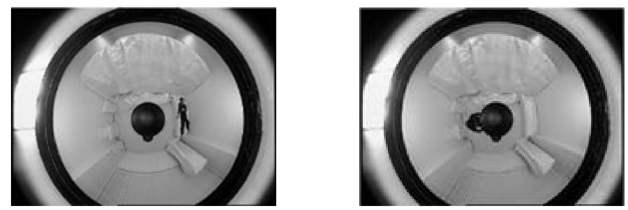
Fig. 10. Abnormality detection procedures based on fuzzy inference.

IV. EXPERIMENTS

In this chapter, some basic experiments of non-daily behavior pattern detection in the experimental monitoring room by a young subject will be conducted because it is difficult to try practical monitoring experiments in real elderly people's homes. The image size is 240×320.

A. Daily behavior pattern learning

In this study, 14400 images representing one day usual behavior patterns based on the investigated data shown in Table I are captured and fuzzy rules will be determined from these images. Fig.11(a)(b) show some examples of the usual behavior pattern images used for fuzzy rule learning, for example, sleeping on the bed and sitting on the floor to have a meal. Of course these images frequently appear in the learning image sequence.



(a) sleeping on the bed (b) having a meal

Fig. 11. Examples of usual behavior pattern images.

B. Non-daily behavior pattern detection

1) Case I : Sleeping on the bed at night (normal behavior): As an example of the usual behavior pattern, the image sequence including the usual behavior pattern "sleeping on the bed at night" around AM 3:00. Fig.12 shows the possibility distribution inference values. It keeps large value close to 1, so they can be judged as normal pattern.

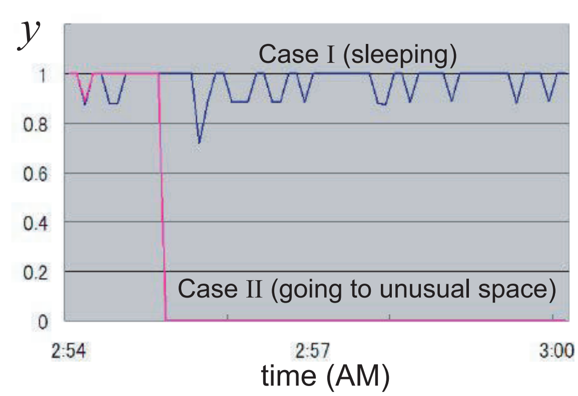
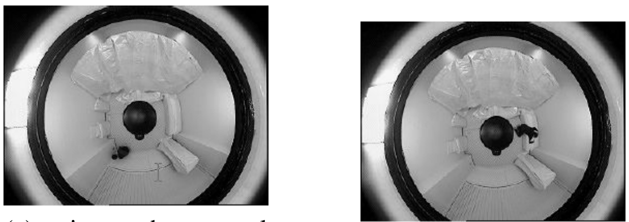


Fig. 12. Possibility distribution inference values of Case I and Case II.

2) Case II : Going to the unusual space (abnormal behavior): As the first example of the unusual behavior detection, the image sequence including the unusual behavior pattern "going to the unusual space" from AM 2:55 is examined. Fig.13(b) shows an example of the captured images of "going to the unusual space" at the left bottom of the room.

Fig.14 shows the possibility distribution inference values. It clearly shows that the unusual behavior patterns can be detected by the proposed algorithm.

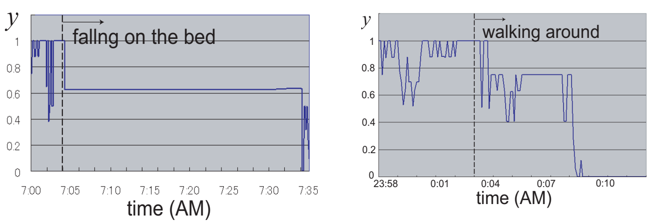
3) Case III : Falling on the bed (abnormal behavior): As the second example of the unusual behavior detection, the image sequence including the unusual behavior pattern "falling on the bed" from AM 7:05 is examined. Fig.13(b) shows an example of the captured images of "falling on the bed".



(a) going to the unusual space (b) falling on the bed

Fig. 13. Examples of unusual behavior pattern images.

Fig.14(a) shows the possibility distribution inference values. It became small, therefore, it is possible to detect the unusual behavior patterns by the proposed algorithm.



(a) Case III (b) Case IV

Fig. 14. Possibility distribution inference values of Case III and Case IV.

4) Case IV : Walking around at midnight (abnormal behavior): As the third example of the unusual behavior detection, the image sequence including the unusual behavior pattern "walking around at midnight" from AM 0:03 is examined. The behavior pattern "walking around" itself is not always unusual, however, it must be unusual if such situation happens at midnight.

Fig.14(b) shows the possibility distribution inference values. It clearly shows that the unusual behavior patterns can be detected by the proposed algorithm.

V. DISCUSSION

This study realized the unusual behavior pattern detection system using an omni-directional vision sensor based on fuzzy inference approach but still has the following important future problems.

- The vision sensor cannot get any information when he/she goes out of the room and when the room is not lighted at night, therefore, some other additional sensors will have to be necessarily applied to this system and to cooperate with the vision sensor. Then a new detection algorithm based on some sensor information will have to be designed.
- Many other feature values, for example, the action speed and direction, the amount of physical activity, will have to be considered to realize the high detection performance and detect other various unusual patterns.
- It must be examined for many kinds of practical rooms after the further detailed analysis of elderly people's behavior patterns in the future work.
- The behavior monitoring system described in this paper can be developed to the cooperation with various motion control systems of robot manipulators supporting elderly people's daily life.

VI. CONCLUSION

This paper proposed a behavior monitoring system to detect the unusual behavior patterns based on fuzzy inference approach. The proposed system automatically learns the usual behavior patterns through the image feature extraction and their pattern appearance frequency as the fuzzy rules and automatically detect the unusual behavior patterns based on the probability distribution inference method. Some experiments based on the detail investigation of the elderly people's typical behavior patterns have shown the effectiveness of the proposed algorithm. Our future work will solve some important problems described in the last chapter.

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