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ADL IDENTIFICATION METHOD WITH DTFRM CONSIDERING THE KNOWLEDGE RADIUS

Bo Shen and Shuoyu Wang

School of Systems Engineering
Kochi University of Technology
185 Miyanokuchi, Tosayamada, Kami, Kochi 782-8502, Japan
{ shen.bo; wang.shuoyu }@kochi-tech.ac.jp

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Abstract. *To provide independent life support for lower-limb disabled people by robots, it is necessary to understand user's activity intention. In the previous study, an activity of daily life (ADL) identification method was proposed based on the distance type fuzzy reasoning method (DTFRM). However, the natural activity motion cannot be repeated all the same every time, especially for the ADL motion with large extent gesture changing. It led to the low accuracy identification of ADL through previous method. In this paper, knowledge radius was introduced for promoting the accuracy of ADL identification. The algorithm of selecting knowledge radius automatically was proposed as well. At last, an ADL identification experiment was conducted by simulated lower-limb disabled people and the result showed the effectiveness of the proposed method.*
Keywords: Independent life support robot (ILSR), Activity of daily living (ADL), Distance type fuzzy reasoning method (DTFRM), Knowledge radius

1. **Introduction.** As the aging society developing around world, age-related disabilities lead many elderly losing the basic ability of living independently. The home-caring for the people who lost the independent live ability is a serious issue of this era. As a home-based solution, the robots, which are capable of assisting elderly and disabled people in relearning how to complete activity of daily living (ADL), are demanded seriously.

However, for most home-caring robots, it is inevitable for users to make operation by remote controllers as joystick. Elderly and disable people have to learn the operation method, which has become the big burden for them. It is highly expected by society that one natural and easy interaction method between home-caring robot and users sprout. Our work aims at the scenery, in which when elderly and disabled people interact physically with the immediate environment at home, home-caring robots are able to provide proper assistance automatically by recognizing user's behaviors and understanding their intentions. Therefore, an activity intention recognition was proposed in the previous research [1,2], by which user's intention of ADL can be recognized. Then, independent life support robot (ILSR) was driven automatically to assist users in completing the ADL task they intend to perform. This method was applied successfully in the vacuuming assistance tasks so that elderly can complete the vacuuming task by focusing on the task only without any intended operation for ILSR. The basic reasoning method was based on distance type fuzzy reasoning method (DTFRM), which is competent for presenting the relationships between human motions and their ADL intentions. Except the ADL identification, DTFRM was also applied successfully in the field like walking intention recognition [3]. However, when the identified categories of ADL increased, the accuracy of ADL identification by previous study method is reduced, especially for the ADL motion with large extent of changing. Consequently, the identification accuracy was unsatisfying for practical independent life assistants by robots. In order to promote the accuracy, knowledge radius was introduced in this study for DTFRM as a series of variable threshold.

In addition to this introductory section, this paper is organized as follows. The elementary information of ILSR and the motion detection system is presented in Section 2. In Section 3, we give the definition of knowledge radius in DTFRM and introduce the condition of deciding knowledge radius in the intention recognition algorithm. In Section 4, an identification experiment of 7 ADLs is implemented to verify the effectiveness. The experimental results are shown in Section 5 with a brief summary.

2. ILSR and the Motion Detection System.

2.1. Independent life support robot (ILSR). In order to provide independent life support for the elderly and the lower-limb disabilities, a series of seat-style life support robot was developed in our laboratory [4]. One of the independent life support robots (ILSR) is shown as Figure 1. By ILSR, we expected to compensate the loss of the basic ability of walking for the people who have difficulties in moving. Therefore, these people can obtain the capability of independent living again.

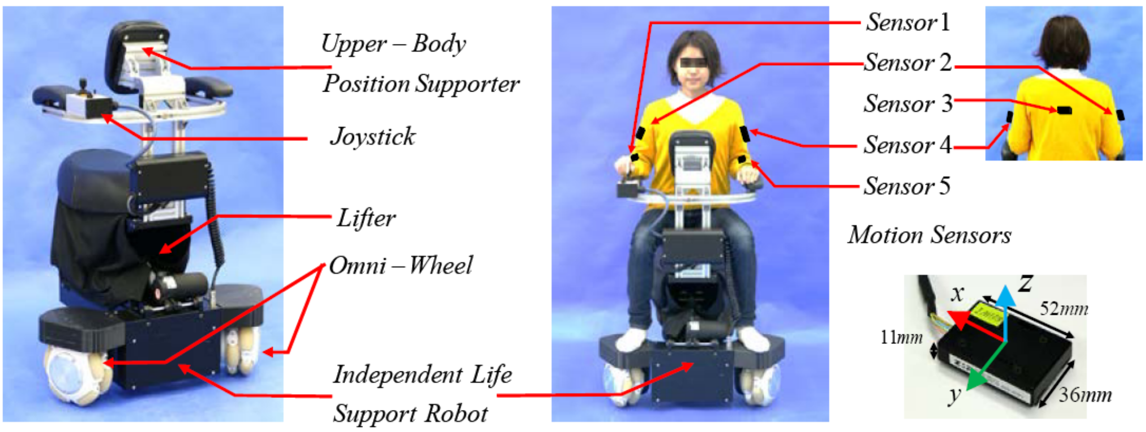

Figure 1. ILSR and the motion detection sensors

Based on the triangle omni-wheels structure and lifter under the seat, the ILSR is able to perform the translation, rotation, and lifting at the same time. The omni directional locomotion abilities of ILSR make its user able to move in the narrow place such as normal home circumstance.

2.2. Motion detection system. As a human, we can figure out the activity other people are doing and even their intention for the next moment by only observing their motions. It is indicated that the motion of us contains the information of the activity we are performing and even the intention. In order to measure the upper body motion of subject during the ADL tasks, a group of wireless motion sensors were applied to measuring the motion information of user's upper body. Considering the motion of upper body can be presented mainly by arms and spine, the sensors were positioned on the middle of each limb and the middle of back as shown in Figure 1.

Inspired by visual identification process of human, the posture of each part of upper body is selected as the input of the reasoning system. Euler angle is one of the most convenient ways to express gesture. However, in order to avoid the drawback of discontinuous data format of Euler angle, a continuation process was executed to express motion features in a normalized and continuous form of value. According to the transformation equation of Euler angles, the continuation process is performed by the following formula:

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta\sin\varphi & \sin\theta\cos\varphi \\ 0 & \cos\varphi & -\sin\varphi \\ -\sin\theta & \cos\theta\sin\varphi & \cos\theta\cos\varphi \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \tag{1}$$

In Formula (1), θ and φ represent the pitch angle and roll angle of body parts where the motion sensors attached on. The gesture of objects can be expressed in the vector form as $\begin{bmatrix} x_{pose} & y_{pose} & z_{pose} \end{bmatrix}^T$. The normalized right forearm motion during lying and vacuuming tasks was shown in Figure 2. For different ADL tasks, the detected motion of upper body is different. Figure 2 shows that it is possible for ADL identification by upper body motion.

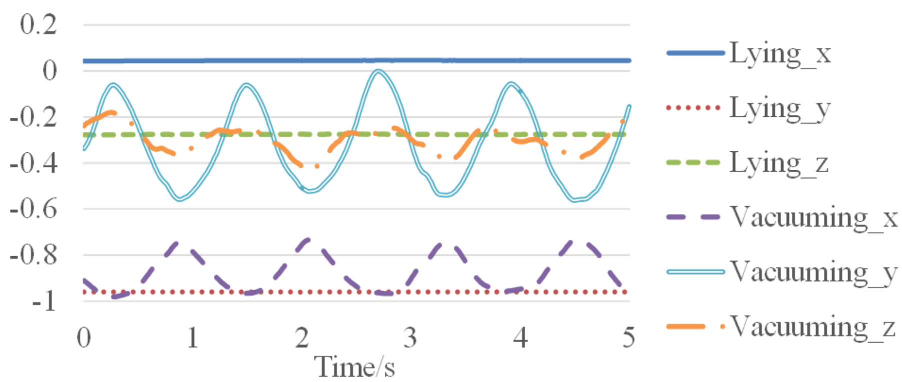

FIGURE 2. The normalized motion information of right forearm

3. **ADL Identification Method Considering the Knowledge Radius.** In the previous research, an ADL identification method was proposed with the DTFRM. As a reasoning method based on fuzzy rules, the user's upper body motion was taken as the attendance of rules, and the consequents were the categories of ADL. Through the fuzzy rules, the relationship between the motions and ADL was described as the reasoning knowledge. During the reasoning process, the similarity between the real-time motion and reasoning knowledge motion was evaluated by the reasoning algorithm according to the distance between them. Finally, the similarity was compared with the predefined threshold parameter to determine whether any ADL was being implemented by subjects. However, the thresholds were the same for each ADL and invariable in previous study. In this section, the knowledge radius was introduced as variable thresholds, and they can be selected according to the learning data set.

3.1. **ADL identification method with DTFRM.** In order to identify the ADL, which subject is doing, the *if-then* rules are presented as follows to describe the relationship between motions and ADL categories.

$Rule^1$: *IF* S_1 is A_1^1, S_2 is A_2^1 ... S_m is A_m^1, *THEN* I is B^1
$Rule^2$: *IF* S_1 is A_1^2, S_2 is A_2^2 ... S_m is A_m^2, *THEN* I is B^2
$Rule^3$: *IF* S_1 is A_1^3, S_2 is A_2^3 ... S_m is A_m^3, *THEN* I is B^3
$\vdots$
$Rule^n$: *IF* S_1 is A_1^n, S_2 is A_2^n ... S_m is A_m^n, *THEN* I is B^n

According to the rules format, S_i represents the current motion of the upper body's ith part, A_i^j represents the motion of the upper body's ith part for $Rules^j$. m is the number of antecedents of each fuzzy rule. I represents ADL user is performing, and B^j represents ADL categories of $Rule^j$, such as (vacuuming, sweeping, and preparing meals). n represents the number of rules in data base.

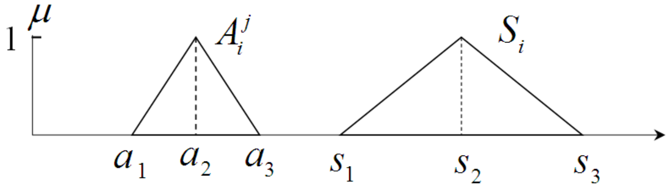

FIGURE 3. Triangular-type fuzzy set expression for attendance of *if-then* rules

As antecedents of each rule, the upper-body motion features A_i^j can be expressed as a fuzzy set according to the statistical features of upper body motion, the mean value *Mean* and standard deviation value *Sd* of real-time motion. In Figure 3, a_2 is at the mean value *Mean* of body part j for task intention B^i, while a_1 and a_3 are $Mean - Sd$ and $Mean + Sd$, respectively.

There are four steps in identifying a user's task intention via the DTFRM.

Step 1: Compute the distance between two fuzzy sets. The distance between triangular fuzzy sets A_i^j and S_i, as shown in Figure 3 is defined as follows:

$$d_i^j = d\left(A_i^j, S_i\right) = \frac{1}{\sqrt{3}} \sum_{h=1}^{2} \left[\sum_{l=1}^{h+1} (a_l - s_l)^2 + \prod_{l=i}^{h+1} (a_l - s_l) \right]^{\frac{1}{2}} \tag{2}$$

Step 2: Compute the distance between fact S and $Rule^j$.

$$d^j = \sum_{i=1}^{m} d\left(A_i^j, S_i\right) \tag{3}$$

Step 3: Perform inference of fuzzy output based on the distances d^j from (3) by the Max-Min fuzzy inference method.

$$(d_{\min}, z) = \min\left\{d^1, d^2, \ldots, d^n\right\} \tag{4}$$

where $d_{\min}$ (d_z) represents the minimum distance and z represents the number of the rules by which the fuzzy distance is minimum with fact S.

Step 4: Determine whether user having any task intention is included in the data base. The reasoning is as follows:

$Rule^0$: *IF* $d_{\min}$ is less than $d_{threshold}$, *THEN* the task intention is B^z.
ELSE task intention is B^0

From *Step 4*, a user's task intention can be identified based on the database. More specially, task intention B^0 represents *No Task Intention*.

In the former research, the parameter $d_{threshold}$ was the same for all the categories of ADL. As a result, the identification process cannot be optimized for each ADL, and the identification accuracy was not satisfying for some of the identifying ADL. In this work, the knowledge radius was introduced to optimize the distance threshold $d_{threshold}$.

3.2. **The knowledge radius.** According to *Step 4* of ADL identification algorithm, the standards of whether a subject is doing an ADL depend on the value of distance $d_{\min}$. It means that the identification algorithm makes decision based on how similar the real-time motions and the motion knowledge extracted in advance are. Thus, the definition of knowledge radius was given as the believe range which if the distance between real-time motion and the motion of rules got into, it was confirmed that the related ADL was being performed.

Definition 3.1. *The knowledge radius of* $Rule^i$ *is a distance* r^i *which can be measured by Equation (2). If the fuzzy distance* d^i *between real motion and motion in the* $Rule^i$ *is less than* r^i, *it is confirmed that the ADL* B^i *is being performed with high possibility.*

In order to evaluate knowledge radius r^i, an optimizing condition is proposed as follows.
Condition 1. *For countable labeled knowledge of upper body motion in ADL, r^i is the minimum value which can guarantee the identification accuracy is equal or higher than p, here $0 < p \leq 1$.*

According to Condition 1, the knowledge radius for each rule can be figured out. Thus, *Step 2* and *Step 4* of ADL identification method can be modified as follows.

Step 2: Compute the distance between fact S and $Rule^j$ relative to knowledge r^j.

$$d^j = \frac{1}{r^j} \sum_{i=1}^{m} d\left(A_i^j, S_i\right) \tag{5}$$

Step 4: Determine whether user has any ADL intention included in the data base. The reasoning process is based on the following rule.

$Rule^0$: *IF* $d_{\min}$ (d_z) is less than R, *THEN* the task intention is B^z.
ELSE task intention is B^0.

In *Step 4*, the parameter R is for adjusting the tolerance range for the condition of intention recognition. In this paper, R was set as 1.0.

4. **ADL Identification Experiments.** To verify the proposed method, an experiment of 7 categories of normal ADL was executed as shown in Table 1. A healthy male volunteer aged 23 yr was instructed to perform each ADL 13 times and 15 seconds each time.

Table 1. Categories of ADL in experiment

No.	Abbr	ADL
$T1$	LY	Lying on bed
$T2$	SOB	Sitting on bed
$T3$	WH	Washing hands
$T4$	VA	Vacuuming
$T5$	CU	Cutting vegetable
$T6$	RSF	Reaching something in front
$T7$	PUS	Picking up something on ground
T	RE	Resting (Not included in database)

The first 3 groups of ADL motion information were selected for determining the knowledge radius r^j. According to Condition 1, the threshold p for knowledge radius selection was set as 1.0 in this work, which means the selected knowledge radius r^j must satisfy all the motion of the selected groups of ADL tasks. The selected knowledge radius r^j is shown in Table 2.

Table 2. Knowledge radius in the experiments

Knowledge Radius	r^1	r^2	r^3	r^4	r^5	r^6	r^7
value	0.04	0.0165	0.0373	0.0914	0.0693	0.0417	0.0588

Applying the extracted knowledge radius of Table 2 in Step 2 proposed in this work, the recognition accuracy is shown in Table 3. As a comparison result, the identification result with the threshold $d_{threshold} = 0.0507$ (the average value of all the selected knowledge radius) is shown in Table 3 as well.

As shown in Table 3, the identification accuracy was promoted generally by applying the knowledge radius in the reasoning process. Especially for the vacuuming task $T4$, the identification accuracy was raised to 8/10 from 5/10. Because upper body motion changes in wider range and angles for vacuuming task, the motion contains more deformation. Therefore, accuracy of ADL identification was reduced by the motion deformations.

TABLE 3. Identification accuracy of experiments

	$T1$	$T2$	$T3$	$T4$	$T5$	$T6$	$T7$
Accuracy without knowledge radius	**8**/10	**9**/10	**10**/10	**5**/10	**8**/10	**9**/10	**9**/10
Accuracy with knowledge radius	**9**/10	**10**/10	**10**/10	**8**/10	**10**/10	**9**/10	**9**/10

However, the same threshold $d_{threshold}$ of previous research limited the tolerance for the motion deformation. For this reason, the accuracy was low without specific threshold for each ADL. With the specific knowledge radius for each task motion, the influence of motion deformation can be alleviated. That is the reason why accuracy of identification was promoted by the introduction of knowledge radius.

5. **Conclusion.** In this study, knowledge radius was proposed for promoting the accuracy of ADL identification. The definition of knowledge radius for ADL identification algorithm and its selecting condition were provided. For satisfying the application of knowledge radius in the algorithm, the reasoning steps were adjusted and shown in this study. Finally, an experiment was implemented and the efficiency of promoting identification accuracy was shown by the experiment.

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