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REAL-TIME IDENTIFICATION OF USER'S ACTIVITY OF DAILY LIVING BY DISTANCE TYPE FUZZY REASONING METHOD

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Abstract. *For the patients with disability of lower-limbs, it is difficult to live independently. On the other hand, the lack of physical exercises of upper body will cause disuse syndrome and undermine their health. In order to provide life support by human support robot (HSR) for lower-limbs handicapped in a health benefit way, a real-time identification method of user's activities of daily life (ADL) is proposed based on analysis of user's upper body motion. A group of motion sensors were attached on user's upper body, including forearms, upper arms and back, to detect upper body motion. Motion of each ADL was expressed in the form of Euler angles, and the features of each motion were extracted by a moving window. According to the extracted motion feature, user's upper body postures and actions for 7 ADLs were described in a set of fuzzy sets to establish ADLs database for identifying the activity which the user is performing. Based on the ADLs database, a fuzzy reasoning method of distance type fuzzy reasoning method (DTFRM) was utilized to recognize user's activity by his upper body motion in real time. In the end, an experiment of identifying 7 daily activities was performed to verify the effectiveness of the proposed method.*
Keywords: Independent life support, Motion intention, Human support robot, Activity of daily life, Fuzzy reasoning

1. **Introduction.** As the increasing of the people who suffer from lower-limb handicapped due to accidents or disease, more and more lower-limb handicapped have to rely on caregiver in daily life. Moreover, as the decreasing of birth rate, quantity of caregiver is decreasing rapidly. If robot can assist their movement in daily life, lower-limb handicapped can live in a comfortable way. In order to provide effective and convenient movement support for the handicapped, an activity of daily living identification method was proposed.

Normally, the elderly and lower-limbs handicapped can make movement on electric wheelchair by hand operation of joystick. If users' movement intention can be identified, robots or electric wheelchair can be operated to provide appropriate movement assistance for them, and their hands can be released to perform activities of daily living. Zhu and Sheng proposed a hand gesture and daily activity recognition method by neural network and hierarchical hidden Markov model in [1]. Shimokawara et al. provided an ADL recognition method for the elderly by considering the location information in [2]. By decomposing elaborate behavior into smaller activities, Patel et al. proposed a method based on HHMM (Hierarchical Hidden Markov Model) in [3]. By fussing information from multi-sensor, Medjahed et al. presented an elderly home monitoring system to learn and recognize ADL in [4]. Stikic et al. presented a weakly supervised recognition method with wearable sensors in [5]. The understanding of human's behavior by robot makes a great promotion of living convenience for the elderly and handicaps.

In our research, a multi-function seat-style human support robot (HSR) for the elderly and the disabilities' independent living was proposed by Wang et al. in [6]. As shown in Figure 1, HSR was designed to perform both rehabilitation training and independent life support. In the former study, the control method has already been investigated [7] and a user's moving intention identification method by weight distribution information was proposed in [8]. However, for daily task assistance, weight distribution information is not sufficient to make identification of user's task intention. Therefore, 5 motion sensors were utilized to detect upper body motion. And then the postures of each part of upper body were presented in form of Euler angles. The statistical features of user's upper body motion were extracted and adopted as the ADL motion database and input of ADLs identification algorithm. For ADL motion database, fuzzy sets were established to describe the upper body motion. In order to perform real-time ADLs identification, a moving data window was applied to extracting upper body motion features. Finally, DTFRM [9] was utilized to identify user's ADLs. 7 activities of daily life related to mobility were adopted in this work.

This paper is organized as follows. In Section 2, setting of motion sensor is introduced. Section 3 describes features extraction method and establishment of ADLs knowledge database by fuzzy set. In Section 4, ADLs reasoning method based on DTFRM is proposed. In Section 5, the experiment result of 7 ADLs identification is discussed. Finally, a brief conclusion is drawn in Section 6.

Figure 1. Human support robot

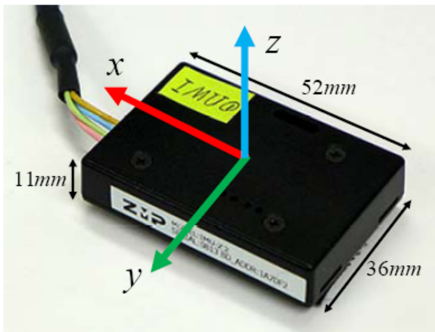

Figure 2. Motion sensor

2. Motion Detection System.

2.1. **Wearable motion sensor.** A group of 9DoF wireless motion sensors, comprising mutually orthogonal tri-axial accelerometers, gyroscopes and magnetometers were used as the sensing platform as shown in Figure 2. 3-axis accelerometers are set in ± 2 g range and tri-axial gyroscopes are set in ± 250 °/s. The sampling frequency is 100 Hz.

2.2. **Sensors placement.** The sensors setup is depicted in Figure 3. 4 sensors were normally positioned in the middle of each limb, and one motion sensor was centered on the back, slightly below the scapula. A sports jacket was implemented to make sure that every sensor can be fixed in sustained position. In this work, the displacements of sensors were neglected by readjusting the position of each sensor every time of experiment execution.

2.3. **Sensors placement.** The raw data from motion sensors is mutually orthogonal tri-axial acceleration, angular velocity and magnetic information. Inspired by human's perception of others' movements or activities, the raw output of motion sensors was transferred into bodies' gesture and pose, which contains more effective information of "what they are doing". Euler angles are utilized to represent user's upper body gesture. Transformation process from raw data of motion sensor to Euler angle is shown as Figure

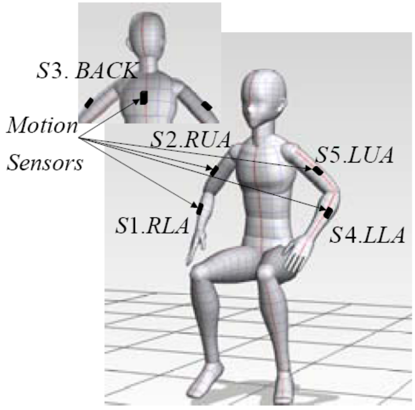

FIGURE 3. Motion sensors position

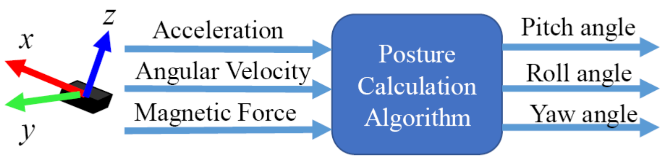

FIGURE 4. Posture calculation and presentation

4. After the transformation, posture of user's upper body was represented by Euler angles with pitch angle, roll angle and yaw angle. However, because of the magnetic inference indoor, the error of yaw was unneglectable during the experiments. In this work, only pitch and roll angles were taken as the input of the identification algorithm. In the next chapter, the features extraction method of ADLs will be introduced.

3. Database Establishment of ADLs.

3.1. Activities to recognize. In order to support lower-limb handicapped to live independently, 7 ADLs were chosen as the recognition activities in this paper as shown as No.1 to No.7 activities in Table 1.

TABLE 1. Activities of daily life to be recognized

No.	Abbr.	ADL
1	LY	Lying
2	SOB	Sitting on bed
3	WH	Washing hands
4	VA	Vacuuming
5	CO	Cooking
6	RSF	Reaching something in front
7	PUS	Picking up something on ground
8	RE	Resting (not belong to database)

Lying and sitting on bed are two of the most regular activities. Under normal conditions, when a user lays on bed, HSR should go and get charged and when a user sits up, HSR should get close to bed to stand by. For washing hands, cooking and picking up something on ground, HSR should keep still to wait for user's next task intention. However, while a user is doing vacuuming, HSR should recognize the behavior and make translation and rotation movement so that the user can complete vacuuming task conveniently. Moreover, for action of reaching something in front (or going forward with something in both hands), HSR should take the user to the place where the user wants to arrive at and stop exactly. The 8th item means that the activity user performing is not included in ADLs database. When HSR comes across this situation, it should keep its position to guarantee user's safety.

3.2. **Feature extraction in real time.** As mentioned in Section 2, only pitch and roll angles were adopted as the input of ADLs identification algorithm. Because there were 5 sensors for motion detection, 10 Euler angles were acquired in total. In order to provide timely life support for user, real-time feature extraction was implemented. As shown in Figure 5, a moving window was applied to extracting motion features. In this paper, moving window's width was set as 1.2s according to the identification performance.

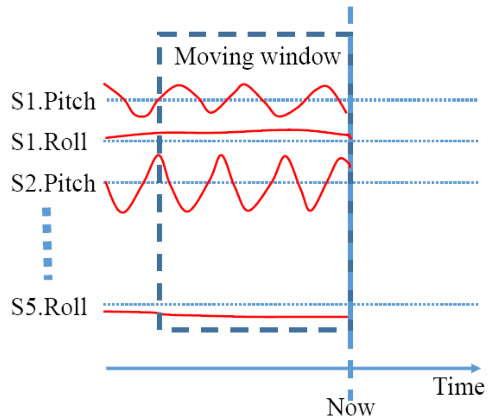

FIGURE 5. Feature extraction

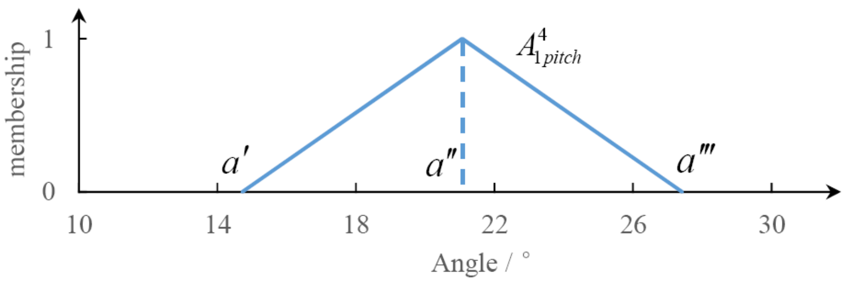

FIGURE 6. Triangular-type fuzzy set expression

3.3. **Feature description by fuzzy set.** Fuzzy theory is efficient in combining information of multi-resources and easy to be applied in depicting signal's features in an understandable way. Therefore, user's motion feature was described by fuzzy set in this paper.

In order to extract motion features, subject was asked to perform every ADL of Table 1 for 10 seconds. The extracted features of vacuuming activity are shown in Table 2.

There are 10 Euler angles with 20 statistic values to describe user's upper body motion during vacuuming activity. Based on the value in Table 2, the features were presented by triangular-type fuzzy set as shown in Figure 6. Triangle fuzzy set has 3 main parameters, a', a'' and a'''. They were respectively defined shown as follows:

$$\begin{aligned} a' &= mean - std.dev \\ a'' &= mean \\ a''' &= mean + std.dev \end{aligned} \tag{1}$$

According to the proposed fuzzy set establishment method, the whole database of 7 ADLs was produced in the form of 70 triangle type fuzzy sets.

Table 2. Feature of vacuuming

Sensor	Euler angle	Angle value/°	
		mean	*std.dev*
S1(RLA)	Pitch	21.06561	6.35316
	Roll	−110.163	3.968213
S2(RUA)	Pitch	−38.7168	10.90934
	Roll	−110.176	4.185308
S3(BACK)	Pitch	−22.3512	0.610126
	Roll	175.2762	1.051423
S4(LLA)	Pitch	26.25986	0.488695
	Roll	−105.652	0.37613
S5(LUA)	Pitch	−57.4249	0.27932
	Roll	−105.073	0.963971

4. Activity of Daily Living Identification by DTFRM.

4.1. DTFRM fuzzy reasoning framework. As a reasoning method, fuzzy reasoning method reflects human reasoning capability based on inaccurate or incomplete data. Therefore, an ADLs reasoning method was proposed based on the distance type fuzzy reasoning method. Figure 7 shows the reasoning framework.

According to the ADLs database established in Section 3, the reasoning algorithm was applied to inferring the activity of user, based on user's upper body motions.

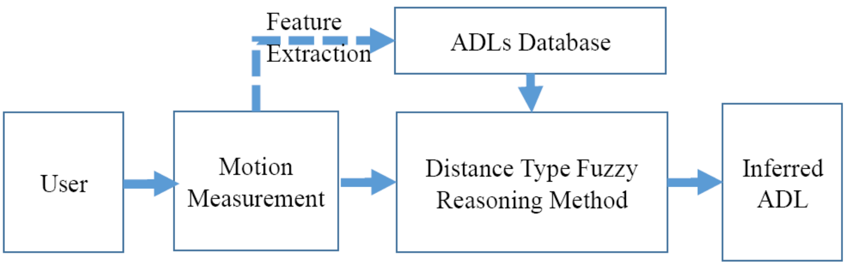

Figure 7. DTFRM fuzzy reasoning framework

Different from Mamdani rules and Takagi/Sugeno rules, DTFRM defines the distance between different fuzzy sets and executes the reasoning (defuzzification) process based on the distance between fact fuzzy set and fuzzy rules. By fusing the reasoning results from every rule, the final result can be concluded, even though there is no interaction between the fact and sparse fuzzy rules of database as shown in Figure 8. When there is no interaction between antecedent and fact, the reasoning result can also be figured out based on the distance between 2 fuzzy sets A_j^i and B. According to the motion feature of each ADL, task motion is always deformed in the real implementation process. That is because human cannot repeat the motion as exact as last time and there is no need to repeat the action as well. As the result, the motion database only describes a general feature of ADL motion, and the error caused by motion deformation can be eliminated by DTFRM in reasoning process. In Section 3, features of every ADL were extracted by experiment for each subject. However, in order to identify user's activity, features were integrated into fuzzy rules as reasoning antecedents. Since there are 7 ADLs to recognize in the work, the fuzzy reasoning process can be presented as follows:

$$\begin{array}{ll} Rule^i: & S_{1pitch} = A^i_{1pitch},\ S_{1roll} = A^i_{1roll}, \\ & S_{2pitch} = A^i_{2pitch},\ S_{2roll} = A^i_{2roll}, \\ & \quad \vdots \qquad \vdots \qquad \vdots \qquad \vdots \\ & S_{5pitch} = A^i_{5pitch},\ S_{5roll} = A^i_{5roll}, \\ & \qquad\qquad \Rightarrow\ y = \beta^i\ i = 1, 2, \cdots, 7 \\ & \\ Fact: & S_{1pitch} = B_{1pitch},\ S_{1roll} = B_{1roll}, \cdots, S_{5roll} = B_{5roll} \\ \hline Result: & \beta \end{array}$$

In order to perform the reasoning process by computer, the calculation method based on the rules is introduced next.

4.2. **DTFRM in ADLs identification.**

Step 1: The DTFRM is built based on the distance information between fuzzy sets. The distance between 2 triangular fuzzy sets in Figure 8, is calculated as Equation (2).

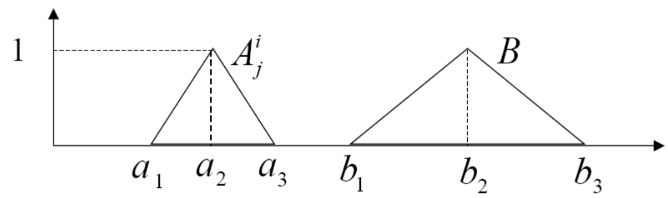

FIGURE 8. Distance between 2 triangle fuzzy sets

Equation (2) defined the distance between fuzzy sets A^i_j and B, and for every rule there are 10 fuzzy sets to be calculated.

$$d^i_j = d\left(A^i_j, B\right) = \frac{1}{\sqrt{3}} \sum_{i=1}^{2} \left[\sum_{j=1}^{i+1} (a_j - b_j)^2 + \prod_{j=i}^{i+1} (a_j - b_j)\right]^{\frac{1}{2}} \tag{2}$$

Step 2: According to Equation (2), the distance between fact and rules for fuzzy set can be figured out. And then the distance between rules and fact should be calculated as follows:

$$d^i = \sum_{j=1}^{5} \left[d\left(A^i_{j\,pitch}, B_{j\,pitch}\right) + d\left(A^i_{j\,roll}, B_{j\,roll}\right)\right] \tag{3}$$

Step 3: Based on fuzzy rules of database in this paper, the relative distance for each ADL can be calculated as:

$$\lambda_i(B) = \frac{\prod\limits_{j=1, j\neq i}^{7} d^i}{\sum\limits_{i=1}^{7} \prod\limits_{j=1, j\neq i}^{7} d^i} \quad i = 1, \cdots, 7 \tag{4}$$

By Equation (4), DTFRM is able to infer a result from the database which consists of sparse fuzzy rules. Therefore, even there are no interactions between rules of the antecedents of ADLs database by sparse fuzzy sets and fact, relative distance can be calculated as well.

Step 4: According to relative distance for each ADL, if-then rule in (5) was implemented to make the decision for whether user is performing any ADL in the database.

According to the experimental result, it was found that when $\lambda_{threshold}$ was around 0.4, the ADLs identification rate is relatively higher than other values. As a result, the threshold value was set 0.4 in this paper to separate the RE intention from other ADLs.

When all relative distances were less than 0.4, it can be identified that user was performing nothing in ADLs database. RE is an inevitable item for safe application of HSR in living assistance. Another if-then rule was utilized to perform the identification of doing nothing.

If the max value of $\lambda_i(B)$ $(i = 1, 2, \cdots, 7)$ is less than $\lambda_{threshold}$, user's ADL is RE.

Else user's ADL is the i-th ADL in Table 1.

5. **Experiment.** To verify the performance of the proposed method of ADLs identification, an experiment of ADLs performing was executed. A healthy male volunteer aged 27 yr and weight 80 Kg was instructed to execute ADLs in Table 1 by the order of lying, sitting on bed, washing hands, reaching something in front, cooking, vacuuming and picking up something on ground. Between every activity, subject operated HSR to the proper position by joystick. According to the complexity of operation actions, applicable interval was set.

During the experiment, subject received activity order from computer by sound. As shown in Figure 9, the orange dot line presents the ADLs order timing from computer. The blue solid line shows the identification result by the proposed identification method. During the 12.6 seconds cooking activity, there was 4.7s identification mistakes which was identified as RE for resting. By analyzing experiment data, the identification error of cooking activity (CO) was caused by the frequency of actions of big difference with the database activity. During the 4.7s interval of cooking task, subject repeated the cooking action in a larger range than usual. When subject performed vacuuming action, there were also about 6s delay. Reference to the experimental video, the error for vacuuming task was caused by a delay of user action at the very beginning.

According to time length of result and real action of ADLs, a summary of identification result is in Table 3. As you can see, the identification rate of CO is only 52.56% in the

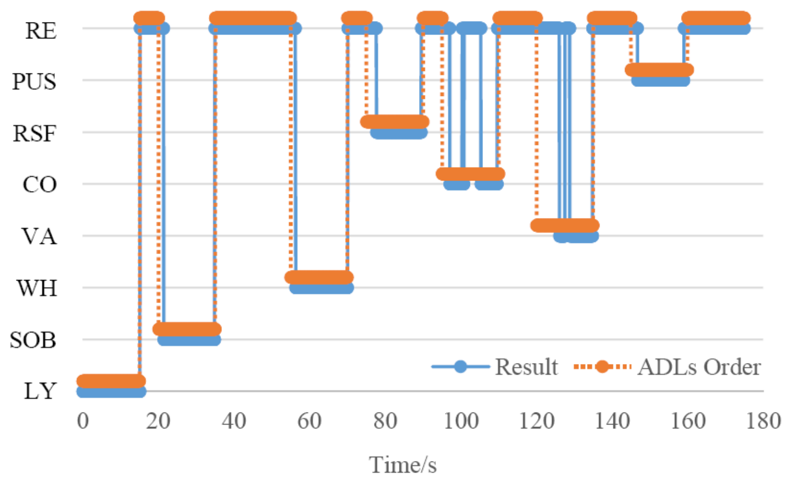

FIGURE 9. Identification result in experiment

TABLE 3. Accuracy time occupation rate

No.	Abbr.	Accuracy
1	LY	100%
2	SOB	89.74%
3	WH	91.02%
4	VA	82.86%
5	CO	52.56%
6	RSF	78.63%
7	PUS	81.62%

experiment. In future work, frequency and more motion features will be considered to promote recognition accuracy of ADLs.

6. **Conclusion.** In this paper, a real-time ADLs identification method by DTFRM was proposed to provide independent life support for lower-limb handicapped. 7 ADLs were taken as identification ADL. ADLs database was established according to the motion feature extracted from upper body gesture. An experiment of series of ADLs was performed to verify the identification performance of the proposed method. The real-time identification result showed that the proposed method can perform the identification of the ADLs in the list in a satisfying correction rate for most activities. However, for some task as cooking, the identification accuracy is only around 50%. In the future work, more rules will be applied to promoting identification rate, and planning method of movement assistance action of HSR will be investigated.

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