RFID-Based Danger Prevention for Home Safety

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***Abstract*—Certain locations and objects at home can easily cause dangerous situations for elders over 65 and kids under 14. It is desired that the caregiver is warned when elders or kids get close to these locations or objects to prevent dangerous situations. In this research, we developed a system for such a purpose. An active RFID tag is attached to each location and each object. The elder or kid carries an RFID reader which detects the signal strengths (RSSI values) of all tags and transmits them to the system in a computer in real time. The system issues a warning to the caregiver when the dangerous degree is above the predefined threshold. A dangerous situation can be prevented if the caregiver watches out beforehand. The dangerous degree is determined through fuzzy inference on RSSI values and the user age. A feedback mechanism is also designed to provide personalized services. Experimental results demonstrate that the system is useful.**

Keywords–RFID; fuzzy inference; user feedback; home safety; ambient intelligence

I. INTRODUCTION

According to the 2008 mortality report published by the Department of Health, Taiwan, the accidental death among children aged from one to fourteen accounts for 26% of all deaths, ranking it as the top cause of death among children. Among accidental deaths, 64% occurred at home, of which 70% could have been avoided. On the other hand, Taiwan has met the WHO (World Health Organization) standard for aged population since 1993. At the end of 2008, the number of elderly people (aged 65 or above) in Taiwan accounts for over 10% of the entire population and is expected to reach 28% by 2050 [1]. Therefore, it has become increasingly important that some automatic mechanisms are developed for homecare. With the help from such mechanisms, children and elders can be better taken care of. In this research, we aim at developing an RFID-based system that can issue warnings to the caregiver when children or elders are getting close to a dangerous object or location at home. Dangerous situations for children and elders can be avoided if the caregiver is warned in advance. This can also reduce the accidental death rate at home.

An RFID (Radio Frequency Identification) system comprises tags with specific codes, a reader, and an antenna. The RFID system functions as the reader sending out radio-frequency waves and triggering the tags within detection range. There are basically two kinds of RFID tags: passive and active. Passive tags simply reflect the signal sent from the reader for the transmission of the stored information (the ID number). They draw power from the reader and need no battery. On the other hand, active tags have their own transmitter and power source (battery). RFID tags are designed to operate in different frequencies. General speaking, lower-frequency tags (usually passive tags) are used in a detecting distance shorter than 0.5 meter; higher-frequency tags (usually active tags) are used for a wider range (several meters to one hundred meters). In this research, we chose the active tag because it has a larger detection range. The wide applications of RFID have influenced people's everyday life. Access control cards and chips for pets are just two of the many applications. The applications of RFID can also be seen in museum exhibits [2], in location positioning systems [3], in inventory management for warehouses [4], and in robots guidance [5] and for guiding people in unfamiliar locations [6].

Because human cognition and the concept of what causes dangers are associated with uncertainty, the concepts of "close" or "very close" have to be determined by the fuzzification (applying fuzzy logic) of uncertain values [7][8]. Computer vision technologies used in home safety have been well-developed, and one could easily monitor the safety of the elderly or children by applying fuzzy inference to image analysis. Unfortunately, installing video cameras in every room of a house is expensive, and the privacy issue is always a major concern [7]. By incorporating RFID in such systems, the cost savings could be substantial. For this study, we utilized the RSSI values of the tags and the age of the user in fuzzy inference [8]. The reason is that the correspondence from the user age and RSSI values to the dangerous degree is fuzzy in nature. Fuzzy membership functions can be easily formulated for them. When deploying active tags in dangerous areas and attaching them to dangerous objects, one's distance to danger can be determined by the strength of the RFID signal, and the degree of danger for users of different ages can be calculated based on the fuzzy theory [9][10]. A sufficiently high degree of danger produced from a set

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of membership functions would trigger the alarm.

In the next section, an overview on related work is given. The system architecture is then presented in Section III. Fuzzy inference and user feedback are the two major issues here. Section IV shows the experimental results. Section V draws a brief conclusion and discusses future development.

II. Related Work

Several studies regarding the application of RFID in healthcare and homecare have been conducted. In 2007, Varshney studied omnipresent care, wherein the wireless Internet and RFID, could help to monitor patients, regardless of their locations [11]. By embedding RFID tags in slippers, Tanaka et al. developed a system to track people in 2007 [12]. Ho et al. developed a reminder system to monitor chronic patients required to take medication and to prevent them from taking the wrong medicine in 2005 [13]. Lai et al. deployed RFID in hospitals to solve medication and patient identification problems in 2007 [14]. To improve health care quality in long-term care centers, Corchado et al. utilized RFID in designing a framework to provide elderly people with individualized nursing care in 2008 [15]. In order to deal with the problem of dementia, Yamahara et al. monitored the behavior of elderly patients by installing multiple RFID tags at their homes in 2008 [16].

The reason that the fuzzy theory is so well suited to widespread applications is that it generates results based on uncertain information. It has been applied and studied in several fields, including the cost-effectiveness of adding drugs to prescriptions [17], the selection of products according to a wide number of variables [18], and to compare the time employees spent working or dawdling [19]. With an RFID-based safety system, even the accuracy of landslide alarms has been improved [20].

III. RFID-Based Danger Warning

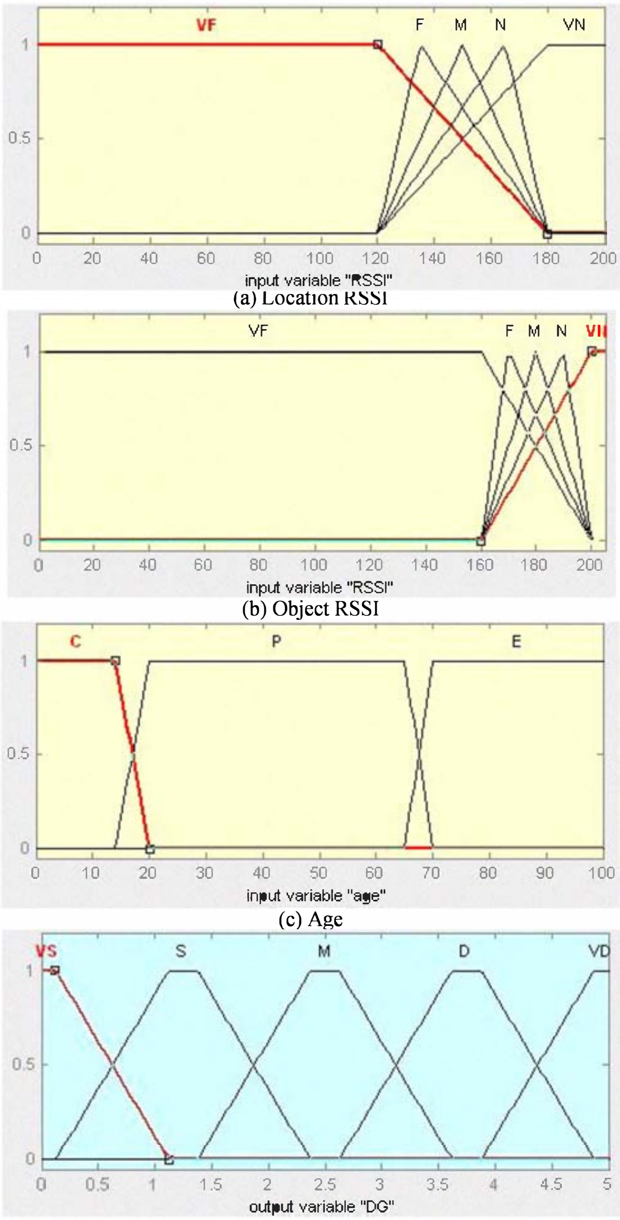
The equipments used in this research included a laptop PC, a PDA with a CF slot, an active CF-RFID reader, a wireless Internet AP, and 18 active tags. We placed 10 tags (solid circle) in dangerous locations and eight tags (hollow circle) on dangerous objects (as shown in Fig.1). A wireless communication environment was established between the PDA/reader and the laptop PC via the wireless AP. We used this test environment to simulate the scenarios that the elders or children approach dangerous locations or objects at home. Based on RSSI values of the active RFID tags received by the system and the age of the user, the degree of danger can be computed.

Figure 1. Test environment.

Only two input variables, the RSSI value and the age, were chosen for the fuzzy membership function, as more variables added would increase the number of fuzzy rules and could have led to incomplete definitions. In our study, there are only 18 RSSI values from 18 different tags. Plus the age of the user, there are totally 19 input variables. This, of course, can be extended into a larger number of rules with a more comprehensive fuzzy rule set. The designed membership functions include the location, the object, the age, and the dangerous degree, where the first three are the input variables and the fourth is the output variable.

Because the same distance from an individual to a location or an object could lead to different degrees of danger, the membership values of locations and objects from the RSSI values are calculated using different membership functions. In Fig. 2, the fuzzy membership functions of the input and output variables are shown. The fuzzy membership functions of location and object have the same five symbols: VF (very far), F (far), M (medium), N (near), and VN (very near), but the corresponding RSSI ranges are different (Fig. 2(a) and 2(b)). The membership function of age has three symbols: C (child), P (prime), and E (elderly) (Fig. 2(c)). It was designed following the definitions of children and elders. Finally, the membership function of dangerous degree has five symbols: VS (very safe), S (safe), M (medium), D (dangerous), and VD (very dangerous) (Fig. 2(d)).

Fig. 3 lists all the fuzzy rules. Fuzzy rules for locations and objects are formulated differently. In this research, we only targeted at the elderly and children. The prime is considered to be safe under any circumstances (Rule 6 of locations and Rule 5 of objects). When elders and children are close to the same dangerous location, the elders should have a better ability to avoid dangerous situation than the children, thus the difference between Rules 4 and 5 in Fig. 3(a). In the object fuzzy rules in Fig. 3(b), there is no such difference (Rule 4 in Fig. 3(b)).



(a) Location RSSI

(b) Object RSSI

(c) Age

(d) Dangerous degree

Figure 2. Fuzzy membership functions.

In this system, we chose the Mamdani-style fuzzy inference with the max-min operation [10]. Minimum is used for the AND operation in each rule and maximum is used for the combination of the results from multiple rules. Moreover, the center of gravity is used for defuzzification of the output variable – the dangerous degree which is ranged from 0 to 5. When the defuzzified dangerous degree is over a predefined threshold, the system issues a warning to the caregiver.

1. If (RSSI is VF), then (DG is VS)
2. If (RSSI is F), then (DG is S)
3. If (RSSI is VN), then (DG is VD)
4. If (RSSI is N) and (Age is C), then (DG is VD)
5. If (RSSI is N) and (Age is E), then (DG is D)
6. If (Age is P), then (DG is VS)
7. If (RSSI is M), then (DG is M)

(a) Locations

1. If (RSSI is VF), then (DG is VS)
2. If (RSSI is F), then (DG is S)
3. If (RSSI is VN), then (DG is VD)
4. If (RSSI is N), then (DG is D)
5. If (Age is P), then (DG is VS)
6. If (RSSI is M), then (DG is M)

(b) Objects

Figure 3. Fuzzy rules.

A feedback mechanism was designed because not all dangerous situations would be regarded as dangerous by all caregivers. When a caregiver does not agree with a dangerous warning, he/she can feedback the opinion to the system. Then a right-shifting micro-adjustment can be made on the corresponding membership function. With the adjustment, a closer distance is needed to generate the same dangerous degree next time the same object or location is approached. In our design, the fuzzy membership functions in Figs. 2(a) and (b) shift to the right for 2 RSSI values each time a caregiver gives a feedback of "not dangerous." The default fuzzy membership functions in Figs. 2(a) and (b) can thus be adjusted for personalization.

IV. Experimental Results

The output of the system is the dangerous degree. The ranges of dangerous degrees are very safe (0-1), safe (1-2), medium (2-3), dangerous (3-4) and very dangerous (4-5). In the experiments, we first test the fuzzy rules and fuzzy inference with different distances and ages (inputs) for both location and object tags. The results are shown in Table I. In the table, we can see that the dangerous degree goes down when the distance becomes larger. The dangerous degrees for the user of age 30 are relatively low in all cases. When the distance is 0 cm (with the RSSI value = 236), the dangerous degrees for both the location and the object are high if the user is at the age of 5 or 70 (4.63 and 4.62). When the distance is 60 cm (with the RSSI value = 181), there is a difference between the dangerous degrees of the location and the object if the user is at the age of 5 or 70 (4.64 and 2.55). This is due to the difference between the fuzzy membership functions for location and object in Figs. 2(a) and (b).

TABLE I. Inferred Dangerous Degrees For Both Location And Object With Various Ages And Distances

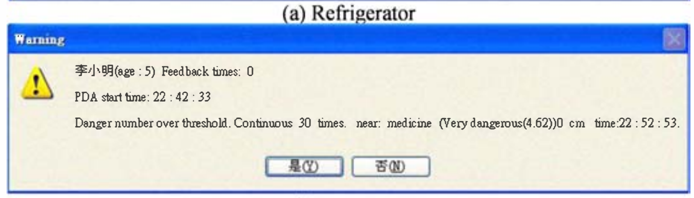
cm/RSSI Age	0/236		30/191		60/181		90/171		120/162	
	Location	Object	Location	Object	Location	Object	Location	Object	Location	Object
5	4.63	4.62	4.64	3.05	4.64	2.55	3.05	2.06	2.67	1.27
16	3.20	3.18	3.24	2.99	3.24	2.55	2.83	2.06	2.57	1.27
30	2.46	2.43	2.50	2.69	2.50	2.40	2.40	2.01	2.28	1.27
67	2.74	2.72	2.78	2.81	2.78	2.49	2.73	2.06	2.54	1.27
70	4.63	4.62	4.64	3.05	4.64	2.55	3.22	2.06	2.88	1.27

To determine the threshold for issuing warnings, we measured the dangerous degrees for five safe situations: watching TV, using computer, sleeping, changing clothes and eating. The highest inferred dangerous degree we got was 2.41. In order to reduce the number of false alarms, we added 1 to this number and used the result (3.41) as the threshold. If the user only gets close to the dangerous location or object for a very short period of time, it would not be considered dangerous. Therefore, the dangerous degree needs to be over the threshold for at least 60 seconds for a dangerous location or 30 seconds for a dangerous object for the warning message to be sent to the caregiver. Our system collected the RSSI values from the active RFID tags once per second.

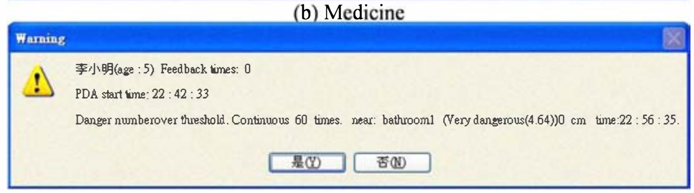
Next, we tested the system with real movement data in the test environment (Fig. 1). We have tested several routes/movements. Here the results of one of them are presented. The user moved from the living room to Bathroom I in the test route: Living room (2 minutes) → Refrigerator (open, 4 minutes) → Computer (3 minutes) → Taking medicines (2 minutes) → Kitchen (1 minute) → Bathroom1 (4 minutes). The user is assumed to be a five-year-old kid. Three warnings were issued during the user movement (Fig. 4). The first warning was issued when the user stayed in front of the refrigerator for 60 seconds. The second one was issued when the user was very close to the medicines for 30 seconds. The third one was issued when the user was close to Bathroom I tag for 60 seconds. These warnings were issued as expected.

Finally, we tested the user feedback mechanism. Assuming that the caregiver thought that the kid was not dangerous in bathroom1, he/she gave feedbacks to the same warning messages for bathroom1 three times. The fuzzy membership function of the Bathroom I tag was thus adjusted. After this adjustment, we tested the same moving route again. Only two warnings were issued then (for the refrigerator and the medicines). The warning message for Bathroom I disappeared because of the feedbacks (Fig. 5).

(a) Refrigerator

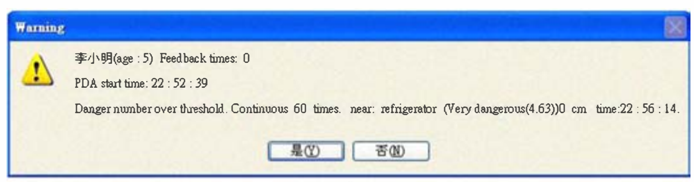


(b) Medicine

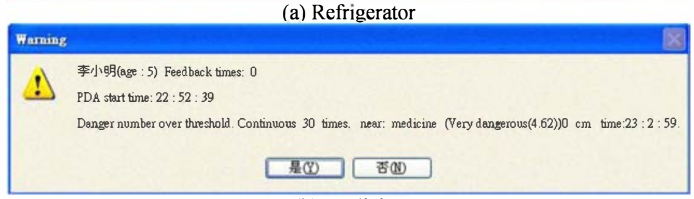


(c) Bothroom I

Figure 4. Issued warnings before user feedbacks.



(a) Refrigerator



(b) Medicine

Figure 5. Issued warnings after user feedbacks.

V. Conclusion And Future Work

A RFID-based system was developed for home safety. Dangerous situations for both elders and the children can be avoided through warning issuing to the caregiver. Fuzzy rules and fuzzy inference are used in the system. Default fuzzy membership functions were set for both dangerous locations and objects. The membership functions can be adjusted for personalization via a user-feedback mechanism. We have tested the system only in a home environment. However, it can be applied to other facilities like daycare centers, kindergartens, and rest homes.

The fuzzy membership functions and the fuzzy rules were designed without consulting any domain experts. It is desired that this can be corrected in the future. We believe that with more domain knowledge, the system will be able to have an even better performance. Nevertheless, the results shown in this paper demonstrate that this approach is useful. Finally, a custom-designed, light-weighted RFID reader with wireless communication capability is needed in real applications. This certainly is not so difficult to be done with the current IC technology.

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