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Front-Door Event Classification Algorithm for Elderly People Living Alone in Smart House Using Wireless Binary Sensors

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ABSTRACT Many elderly persons prefer to stay alone in a single-resident house for seeking an independent life and reducing the cost of health care. However, the independent life cannot be maintained if the resident develops dementia. Thus, an early detection of dementia is essential for the elderly to extend their independent lifetime. Early symptoms of dementia can be noticed in everyday activities such as front-door events. For example, forgetting something when the person leaves the house might be an early symptom of dementia. In this paper, we introduce a novel front-door events [exit, enter, visitor, other, and brief-return-and-exit (BRE)] classification scheme that validated by using open data sets ($n = 14$) collected from 14 testbeds by anonymous wireless binary sensors (passive infrared sensors and magnetic sensors). BRE events occur when four consecutive events (exit-enter-exit-enter) happen in certain time intervals (t_1, t_2, and t_3), and some of them may be the forget events. Each testbed had one older adult (aged 73 and over) during the experimental period ($\mu = 547.6 \pm 370.4$ days). The algorithm automatically classifies the resident's front-door events. Experimental results show the events of total exits, daily exits, out-time per exit, as well as the significance of the t_i parameters for the number of classified BRE events. Since part of the BRE events may be the forget events, the proposed algorithm could be a useful tool for the forget event detection.

INDEX TERMS Binary sensors, device-free, elderly monitoring, front-door events, forget event.

I. INTRODUCTION

The elderly population (aged 65 and beyond) of the developed countries has drastically increased over the last few decades, which results in various kinds of problems and challenges for society (e.g., a health care burden and shortage of caregivers.) Furthermore, the number of people living alone at home [1], [2] and the number of single-resident houses [3] are also increasing worldwide. It is reported that elderly persons prefer an independent and aging-in-place lifestyle due to the high expense of health care services and the privacy concern while living with a caregiver [4]. However, the independent life cannot be maintained if the person has dementia. Dementia development can be delayed or even reversed (in case of reversible-dementia) if the elderly can be properly treated in the early stage of dementia [5]. Thus, the early detection of dementia is very important for the elderly living alone, since it can increase the possibility of prolonging an independent life for elderly people.

One of the earliest dementia symptoms is memory lapses. For example, the person mislays an item, or leaves the lights on, or struggles to remember why he/she enters a certain room [6], or forgets something (e.g., a phone, a wallet) when he/she leaves a home. To our best knowledge, we have not found any work in the literature review that detects the forget event when the person leaves a home. This motivates us to develop a novel device-free non-invasive front-door events classification algorithm for the forget detection.

II. BACKGROUND

In the past two decades, several dementia detection schemes for indoor daily-life activities using wearable devices [7]–[12], stationary sensors (e.g., camera) [13], and device-free non-invasive anonymous binary sensors (e.g., passive infrared sensors (PIR), and magnetic switches) [5], [14]–[17] have been proposed. Cameras have a bad reputation due to its privacy invasion, and one third of the people who own a wearable tracker stopped using the tracker within a six months because of its natural flaws. For example, the device can be lost easily; its battery life is short, and wearing it is uncomfortable [19]. Therefore, device-free non-invasive systems are probably the most preferable for a long-term monitoring application.

Akl *et al.* [5] and Dodge *et al.* [14] have suggested an early stage dementia detection method based on an indoor walking speed as well as its variability using PIR sensors placed in series on the ceiling. Dawadi *et al.* [15] have developed an unobtrusive automatic machine-learning algorithm to assess cognitive health of a person by assessing the completeness of the task which a person is given using binary sensors in the smart house. Das *et al.* [16] have proposed a real-time automatic activity error classification model for dementia detection using binary sensors in the smart house. Petersen *et al.* [17] have presented an unobtrusive, cognitive, emotional, and physical state assessment method based on the time out-of-home. And the results of this study revealed that the person who spent more hours outside the home was more likely to have a better cognitive function.

For the time being, device-free non-invasive dementia detection appears to be a rather new research area; a handful of recent studies have proposed such schemes for daily life activities including walking speed [5], [14], completeness of task [15], [16], and time out-of-home [17] using anonymous binary sensors. However, there is no scheme for classifying front-door events from daily life activities for the purpose of the forget event detection.

The main objective of this paper is to classify front-door events of a resident in the smart house using device-free non-invasive wireless binary sensors. We summarize our contributions of this study as follows:

- We introduce the front-door events classification algorithm for the elderly people living alone;
- We propose a novel brief-return-and-exit (BRE) event as a new measure for the non-invasive forget event detection; however, further research is needed for the validation of the forget event detection;
- For the first time, we extract the front-door events from an open dataset collected during a long-term real-life experiment in the smart house using non-invasive wireless binary sensors.

III. METHODS

Fig. 1 illustrates a block diagram of the proposed scheme of detecting the front-door events with a BRE percentage analysis using raw data collected via non-invasive wireless binary sensors. As shown in the figure, classification consists of two steps. The first step classifies exit and enter events from the raw data. The second step classifies the BRE events based on the occurrence of the exit and enter events.

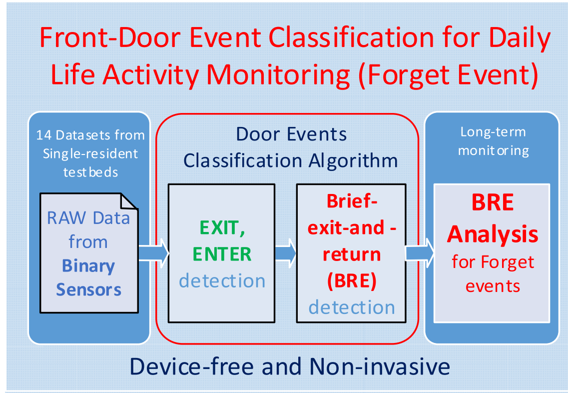

FIGURE 1. Block diagram of the front-door events detection and trend analysis.

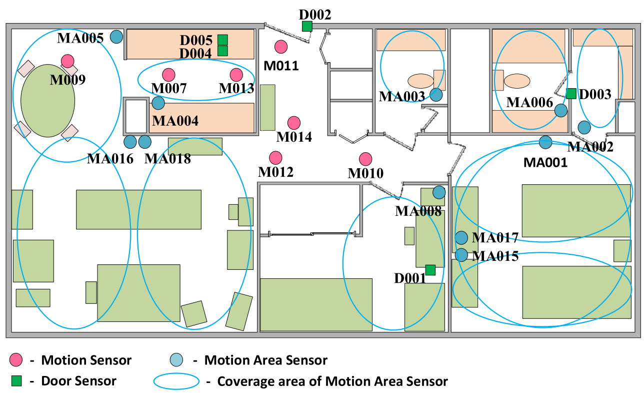

FIGURE 2. Layout of the HH118 testbed in CASAS project.

A. TESTBEDS

Fourteen testbeds (HH102, HH104, HH106, HH107, HH112, HH113, HH115, HH116, HH117, HH118, HH120, HH123, HH124, and HH130) out of 25 "Horizon House" testbeds from Washington State University's Center for Advanced Studies in Adaptive Systems (CASAS) project [20] are chosen for this study. CASAS is a long-term project concerning the automatic recognition of human activities and daily life events in the smart home using non-invasive binary sensors, which offers open datasets for research groups. The project has the ethical approval from their institutional review board. Fig. 2 illustrates a layout and locations of binary sensors of HH118 testbed. There was one resident (aged over 73 years) living in each testbed. There is no information in the dataset about the resident's exact age, sex, cognitive state, activity level, and the like. Each testbed, equipped with more than 20 wireless binary sensors [21], has a kitchen, a dining area, and at least one bathroom and one bedroom.

B. BINARY SENSORS

All binary sensors have ZigBee wireless module to connect with the server by a wireless sensor networks [22], [23].

In Fig. 2, motion sensors (M0XX), motion area sensors (MA0XX), and door sensors (D00X) are represented by a pink circle, a blue circle, and a green square, respectively. M0XX is a PIR sensor that is fixed on the ceiling for the purpose of sensing movements under it. MA0XX is a PIR sensor which senses movements within the coverage area shown by a blue oval in the figure. These motion sensors send a simple "ON" message when motion is present, followed by an "OFF" message a short time after the motion is stopped. D00X is a magnetic sensor to sense whether the door is open or not. They are usually mounted on strategically important doors throughout the testbeds. They send "Open" or "Close" messages when the door is opened or closed.

TABLE 1. Datasets specifications.

Testbed	Experimental duration	Days	Number of Events
HH102	2011/06/13 - 2014/04/16	1039	6'567'564
HH104	2011/06/09 – 2013/09/04	732	6'626'042
HH106	2011/06/14 – 2014/12/31	1297	5'840'635
HH107	2012/08/01 – 2013/7/25	359	3'243'314
HH112	2011/06/13 – 2011/10/31	141	850'030
HH113	2011/06/13 – 2012/05/11	512	3'245'708
HH115	2011/06/15 - 2012/05/25	346	2'263'107
HH116	2011/06/07 – 2011/11/18	165	590'309
HH117	2011/06/13 – 2011/05/25	348	1'130'775
HH118	2011/06/14 - 2014/04/20	1042	7'674'869
HH120	2012/02/01 – 2013/12/31	700	2'535'867
HH123	2013/03/01 – 2014/10/09	588	2'907'282
HH124	2013/03/01 – 2013/07/25	147	175'721
HH130	2014/04/17 – 2014/12/23	251	1'168'862

C. DATASETS

The datasets shown in Table 1 were collected during 2011-2014, with different experimental periods ($\mu = 547.6 \pm 370.4$ days), and various numbers of events ($\mu = 3.2 \pm 2.5$ millions). Event logs are saved chronologically, and each event log consists of four parts, i.e., date, time, sensor, and status. Typical samples of dataset of HH118 are shown in Fig. 3. According to these samples, we can realize that the resident went to the door from the coverage area of MA018 through the location of M012, and then opened the door, finally closing the door. We could assume that the resident is leaving the house since M011 sends "OFF" message after the door is closed.

In this paper, we assume that all the event logs are true and positive since no video recordings or complete annotations are offered with the dataset for the validation.

D. FRONT-DOOR EVENTS

We define five types of front-door events for the residents who live alone. Table 2 shows the front-door events and corresponding sequences of sensor logs. "M", "(No M)", "OPEN", and "CLOSE" are separately representative of "any movement inside the house", "no movement inside the house", "opening of the door", and "closing of the door". Exit event starts with "M" and is followed by "OPEN", "CLOSE", "No M" and finally ends with "OPEN". Enter event starts with "(No M)", because there would not be any motion activity when the resident is not inside, and then is followed by "OPEN", "M", "CLOSE", and "M". VISITOR event happens when visitors (or delivery men) come and go, and its first three events are same as in the EXIT event. Thus the algorithm needs to await the fourth sequence to make sure the event was VISITOR or EXIT.

Date	Time	Sensor	Status
2011-11-04	09:40:23.708148	MA018	ON
2011-11-04	09:40:24.104128	M012	ON
2011-11-04	09:40:24.302148	MA018	OFF
2011-11-04	09:40:26.816524	M011	ON
2011-11-04	09:40:27.408132	M012	OFF
2011-11-04	09:40:27.642225	D002	OPEN
2011-11-04	09:40:29.543298	D002	ClOSE
2011-11-04	09:40:30.428122	M011	OFF

FIGURE 3. **Typical samples of raw data.**

TABLE 2. **Front-door events and their sequence of sensor logs.**

Door event	Sequence of sensor logs
EXIT	M OPEN CLOSE (no M) OPEN
ENTER	(No M) OPEN M CLOSE M
VISITOR	M OPEN CLOSE M
OTHER	(No M) OPEN CLOSE OPEN
BRE	EXIT ENTER($<t_1$) EXIT($<t_2$) ENTER($>t_3$)

In case of a visitor who comes and goes, there is a movement in the house either before or after the door opens and closes. On the contrary, when the resident gets out of the house, there is no movement inside the house and the next sensor log must be "OPEN" resulting from the resident who opens the door from the outside when returning home. OTHER event happens when the door opens from the outside and closes without anyone entering the house, and then the door is opened again after certain time.

The last front-door event is a brief-return-and-exit (BRE) event which occurs when four consecutive events happened in some certain time intervals ($t_1 < 20$ min, $t_2 < 20$ min, and $t_3 > 30$ min). The first step is EXIT event. The second step is ENTER event which happened within t_1 min after the previous exit. The third step is EXIT event which happened within t_2 min after the previous enter. Finally, the fourth step is ENTER event which happened more than t_3 min after the previous exit. We assume BRE may reveal the incident that the resident forgets something when he/she leaves home. For example, in case of $t_1 = 5$ min, $t_2 = 5$ min, and $t_3 = 30$ min, the resident realizes that he/she forgets something and returns within 5 min after leaving home and leaves again within 5 min, and finally comes back home after more than 30 min.

Algorithm 1: EXIT, and ENTER events classification

```
1:  for all sensor logs in the dataset:
2:     if any movement occurs in the house:
3:        if door_status = Close and possible_enter = Yes:
4:           label "ENTER" for previous CLOSE event
5:           possible_enter = No
6:           calculate out_time
7:           call checkBRE()
8:        else return
9:     else if door is opened:
10:       door_status = Open
11:          if possible_exit = Yes:
12:             label "EXIT" for previous CLOSE event
13:             possible_exit = No, possible_enter = Yes
14:             calculate in_time
15:             call checkBRE()
16:          else: possible_exit = Yes
17:    else door is closed:
18:       door_status = Close
```

Algorithm 2: BRE event classification

```
1:  checkBRE():
2:    if ENTER event is occurred:
3:       if BRE_step = 1 and out_time < t1
4:          BRE_step = 2
5:       else if BRE_step = 3 and out_time > t3
6:          label "BRE" for the last ENTER event
7:       else: BRE_step = 0
8:    else EXIT event is occurred:
9:       if BRE_step = 0:
10:         BRE_step = 1
11:      else if BRE_step = 2 and in_time < t2:
12:         BRE_step = 3
13:      else: BRE_step = 0
```

FIGURE 4. Door events classification algorithms.

E. FRONT-DOOR EVENTS CLASSIFICATION ALGORITHM

Front-Door events classification algorithm is illustrated in Fig. 4 in the form of a pseudocode. The algorithm respectively takes the sequence of sensor logs, $E_1, E_2, \ldots, E_n$ $(n \in \mathrm{N})$, as real-time inputs and outputs $E_1, E_2, \ldots, E_n$ $(n \in \mathrm{N})$, as real-time inputs and outputs considering "EXIT", "ENTER", and "BRE" as labels for the front-door events. Algorithm 1 is for EXIT and ENTER events classification, and Algorithm 2 is for BRE event classification.

Algorithm 1 runs at the following events: any movement inside the house (line 2), opening of the door (line 9), and closing of the door (line 17). Variables *out_time* and *in_time* are used for calculating the time duration between consecutive exit-enter, and enter-exit, respectively. Variables *possible_enter*, *possible_exit*, and *door_status* are used for distinguishing EXIT and ENTER events from VISITOR and OTHER events. Parameters t_1, t_2, and t_3 are for BRE event detection. In case the door is closed (line 17), the algorithm updates the door status. In case of a movement inside the house, the algorithm checks if the door is closed and the *possible_enter* is "Yes" (line 3), and if both conditions are true then the algorithm labels the previous close event as "ENTER". Moreover, checkBRE function will be called (line 7) after *out_time* is calculated (line 6) and *possible_enter* is set to "No" (line 5). In case the door is opened (line 9), the algorithm updates the door status (line 10) and labels the previous close event as "EXIT" if *possible_exit* was "Yes" (line 11), then checkBRE function will be called (line 15) after *in_time* is calculated, *possible_exit* is set to "No", and *possible_enter* is set to "Yes" (line 13). Otherwise the algorithm assumes that the current open event was the beginning of exit, and thus sets *possible_exit* as "YES" (line 16).

BRE event classifier has a step counter (BRE_step) that is incremented by one (lines 4, 10, and 12) when corresponding step condition is satisfied, otherwise the counter is set to zero (lines 7 and 13). The first step takes place when the counter is zero and exit occurs (line 10); the second step takes place when the counter is one and enter occurs within t_1 min after the previous exit (line 4). The third step takes place when the counter is two and enter occurs within t_2 min after the previous enter (line 12). BRE event will be finally detected when the counter is three and the next enter occurs more than t_3 min after the previous exit (line 6).

F. STATISTICAL ANALYSIS OF BRIEF-RETURN-AND-EXIT PERCENTAGE

The number of total BRE events can vary with different value of t_i parameters. A BRE percentage given in (1) is used for BRE event analysis.

$$BRE\ percentage = \frac{N_{BRE}}{N_{Exit}} x100 \tag{1}$$

where N_{BRE} is a total number of BRE events in a month/weekday, and N_{Exit} is a total number of exits in a month/weekday.

Monthly/weekday's mean (2), standard deviation (3), correlation coefficient (4), and coefficient of variance (5) of the three variables (N_{Exit}, N_{BRE}, and $BRE\ percentage$) are calculated as follows:

$$\mu = \frac{\sum_i x_i}{n} \tag{2}$$

$$\sigma_x = \sqrt{\frac{1}{n}\sum\nolimits_i^n (x_i - \mu)^2} \tag{3}$$

$$\rho_{xy} = \frac{\sigma_{xy}}{\sigma_x \sigma_y} \tag{4}$$

$$CV = \frac{\sigma}{\mu} * 100\% \tag{5}$$

where i is the index of a month/weekday, n is a total number of months/weekdays, x_i is the value of three variables (N_{Exit}, N_{BRE}, and $BRE\ Percentage$), and σ_{xy} is the covariance of any two variables.

G. ALGORITHM VALIDATION

All detected front-door events are logged in a csv file with their parameters i.e. date, timestamp, and t; t indicates the time interval between the front-door events (see Fig. 5). In the figure, a BRE event is detected at the third row from the bottom, and EXIT and ENTER events of the BRE event are detected in the fourth column followed by t parameters on

1	Date	Timestamp	Door Sensor	Door Event	t [min]
786	8/21/2013	8:56:22 AM	OPEN		
787	8/21/2013	8:54:46 AM	OPEN	EXIT Start	136.2
788	8/21/2013	8:54:52 AM	CLOSE	EXIT End	
789	8/21/2013	8:56:27 AM	CLOSE		
790	8/21/2013	8:56:22 AM	OPEN	ENTER Start	1.5
791	8/21/2013	8:56:27 AM	CLOSE	ENTER End	
792	8/21/2013	8:58:10 AM	OPEN		
793	8/21/2013	8:58:15 AM	CLOSE		
794	8/21/2013	5:03:28 PM	OPEN		
795	8/21/2013	8:58:10 AM	OPEN	EXIT Start	1.8
796	8/21/2013	8:58:15 AM	CLOSE	EXIT End	
797	8/21/2013	5:03:34 PM	CLOSE		
798	8/21/2013	5:03:28 PM	OPEN	ENTER Start	485.2
799	8/21/2013	5:03:34 PM	CLOSE	ENTER End	
800	8/21/2013	5:03:28 PM	OPEN	BRE	
801	8/21/2013	7:04:15 PM	OPEN		
802	8/21/2013	7:04:20 PM	CLOSE		

FIGURE 5. Raw data samples of a BRE event classified from HH118.

the fifth column. At this specified BRE event, $t_1 = 1.5$ min, $t_2 = 1.8$ min, and $t_3 = 485.2$ min. To validate the BRE events, we have manually checked if the parameters of a specified BRE event match the raw dataset.

In Fig. 6, raw samples of the ENTER, EXIT events of the BRE event given in Fig. 5 are illustrated with descriptions on the right half of the figure, and some redundant events were omitted from the figure to minimize the figure. As shown here, the resident gets out at 8:54:51 am, and then comes back at 8:56:21 am after $t_1 = 1.6$ min. The resident gets out again at 8:58:15 am after temporarily entering the living room. Finally, the resident comes back home at 17:03:32 pm after $t_3 = 485.2$ min. Therefore, this BRE event is validated since all parameters are matched.

IV. EXPERIMENTAL RESULTS

Total exits, average exits per day, out-time per exit, total BRE events and BRE events per month at three different time intervals are shown in Table 3. In the table, 20:20:30 indicates $t_1 = 20$ min, $t_2 = 20$ min, and $t_3 = 30$ min.

The resident HH124 make a total of 29 exits on 147 days, and has the lowest daily exit number (0.2), and has the highest average out-time per exit (3.91 hr) among the fourteen residents. The resident HH107 made the highest daily exits (5.92), which makes him/her the most active resident among all of the residents; however, the resident has the third lowest (0.5 hr) out-time per exit. This indicates that the resident stays for a short time when he/she goes out frequently. In addition, the resident has the second highest monthly BER events at both time intervals. HH106 make the highest number of BRE events at both intervals. Residents HH112, HH116, HH117, HH120, HH123, HH124, and HH130, are the seven residents who have the lowest monthly BRE events ($\mu = 4 \pm 2.8$, and $\mu = 0$ at time interval $t_1 = t_2 = 20$, and $t_1 = t_2 = 2$, respectively). Residents HH102, HH106, and HH118 are the residents who have been monitored in the longest experimental period ($\mu = 1026.0 \pm 148.1$ day), and they have

2013-08-21 08:54:45.81 M011 ON		
2013-08-21 08:54:46.35 D002 OPEN	- Exit Starts	
2013-08-21 08:54:51.50 D002 CLOSE	- Exit Ends	
2013-08-21 08:54:52.72 M011 OFF	- No movement	
2013-08-21 08:56:21.63 D002 OPEN	- Enter Begins	t1 = 1.5 min
2013-08-21 08:56:22.17 M011 ON		
2013-08-21 08:56:27.14 D002 CLOSE	- Enter Ends	
2013-08-21 08:56:29.44 M011 OFF		
2013-08-21 08:56:31.20 M014 ON		
2013-08-21 08:56:33.87 M014 OFF		
2013-08-21 08:56:35.04 M012 ON		
2013-08-21 08:56:37.23 MA018 ON	- Entering to Living room	
2013-08-21 08:56:37.38 M012 OFF		
2013-08-21 08:56:39.06 MA016 ON		
2013-08-21 08:56:39.43 MA018 OFF		
2013-08-21 08:56:40.15 MA016 OFF		
2013-08-21 08:56:54.22 MA016 ON		
2013-08-21 08:56:55.01 MA018 ON		
2013-08-21 08:56:55.32 MA016 OFF		
2013-08-21 08:56:57.19 M012 ON	- Leaving the Living room	
2013-08-21 08:56:57.44 MA018 OFF		
2013-08-21 08:56:59.05 M012 OFF		
2013-08-21 08:58:05.68 M014 ON	- Going to the front door	
2013-08-21 08:58:07.53 M014 OFF		
2013-08-21 08:58:09.01 M011 ON	- At the front door	
2013-08-21 08:58:09.97 D002 OPEN	- Exit Starts	
2013-08-21 08:58:15.36 D002 CLOSE	- Exit Ends	t2= 1.8 min
2013-08-21 08:58:15.98 M011 OFF	- No movement	
2013-08-21 17:03:28.39 D002 OPEN	- Enter Starts	t3 = 485.2 min
2013-08-21 17:03:29.04 M011 ON		
2013-08-21 17:03:32.39 D002 CLOSE	- Enter Ends	

FIGURE 6. Raw data samples of a BRE event classified from HH118.

TABLE 3. Statistics of exits and BRE events.

					20:20:30		2:2:30	
Testbed	Total days	Total Exits	Exits/day	Out-time /exit [hr]	BRE events	BRE /month	BRE events	BRE /month
HH102	1039	1193	1.15	0.90	26	0.75	9	0.26
HH104	732	1531	2.09	0.36	17	0.70	8	0.33
HH106	1297	4835	3.73	0.95	156	3.61	36	0.83
HH107	359	2127	5.92	0.50	71	5.93	26	2.17
HH112	141	303	2.15	1.61	2	0.43	0	0.00
HH113	512	1502	2.93	1.35	18	1.05	6	0.35
HH115	346	1234	3.57	0.92	43	3.73	24	2.08
HH116	165	255	1.55	1.10	9	1.64	0	0.00
HH117	348	629	1.81	0.73	5	0.43	0	0.00
HH118	1042	3944	3.79	1.04	84	2.42	4	0.14
HH120	700	2157	3.08	1.12	8	0.34	2	0.09
HH123	588	1200	2.04	1.95	4	0.20	0	0.00
HH124	147	29	0.20	3.91	1	0.20	0	0.00
HH130	251	1368	5.45	0.06	3	0.36	0	0.00
μ	**547.6**	**1593.4**	**2.8**	**1.2**	**31.9**	**1.6**	**8.2**	**1.0**
σ	**370.4**	**1358.1**	**1.6**	**0.9**	**44.3**	**1.7**	**11.8**	**0.7**

about a same out-time per exit ($\mu = 1.0 \pm 0.1$ hr). However, the resident HH118 made 3.29 times more exits per day than the resident HH102 did.

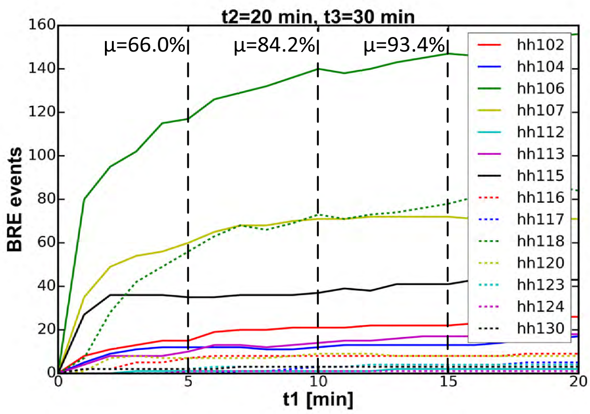

FIGURE 7. BRE events vs. t_1 parameter for all testbeds.

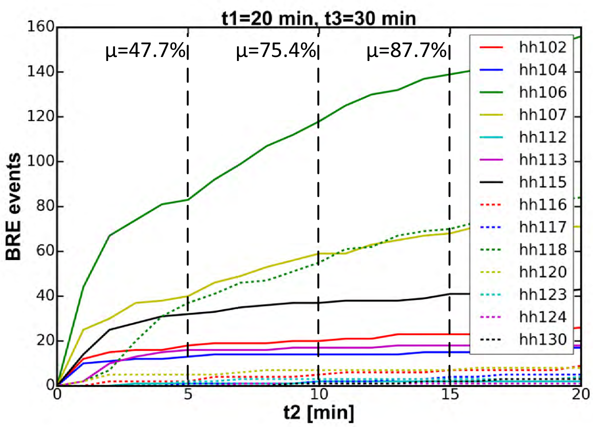

FIGURE 8. BRE events vs. t_2 parameter for all testbeds.

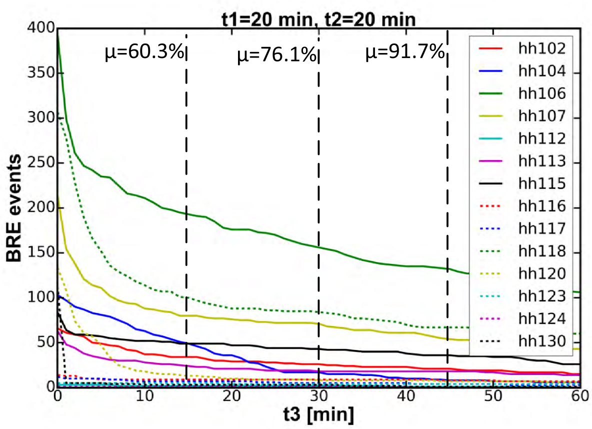

FIGURE 9. BRE events vs. t_3 parameter for all testbeds.

Figs. 7-9 represents the relationships of BRE events and t_i parameters, and we can observe that the number of classified BRE events is quite dependent on t_i parameters. As shown in Fig. 7, 66.0%, 84.2%, and 93.4% of the total BRE events (at $t_1 = 20$ min) of all residents are detected on 5 min, 10 min, and 15 min, respectively. In Fig. 8, similarly, 47.7%, 75.4%, and 87.7% of all BRE events (at $t_2 = 20$ min) are detected on 5 min, 10 min, and 15 min, respectively. In Fig. 9, 60.3%, 76.1%, and 91.7% of all BRE events (at $t_3 = 0$ min) occurred within 15 min, 30, and 45 min, respectively.

A. MONTHLY EXITS, BRE EVENTS, AND BRE PERCENTAGE

Figs.10-12 show, respectively, the monthly exits, monthly BRE events, and monthly BRE percentages of all 14 residents in the form of a density map. Experimental period is represented by months in the x-axis, testbeds are in the y-axis, and monthly exits, monthly BRE events, and monthly BRE percentages are represented by various colors in the z-axis.

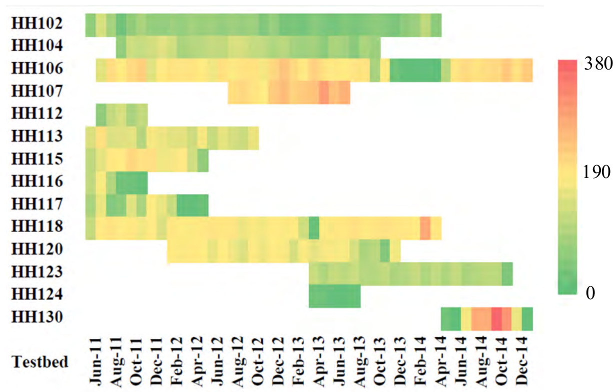

FIGURE 10. Monthly exits shown on a density map.

In Fig. 10, the highest monthly exit value (380) is represented by red, and the lowest value is represented by green. From the density map, we can observe that the resident HH107 is the most active resident in the whole experimental period in terms of the number of exits per month, and he/she became more active in the end of the experimental period. Similarly, the resident HH106, HH118, and HH130 were active persons among the rest; however, they were not constantly active in the experimental periods. For instance, HH118 became more active in the end, and HH130 was extremely active in the middle of the period, and HH106 was not active at all between the end of 2013 and the beginning of 2014. Moreover, HH118 was not active in April 2013. On the contrary, the residents HH116 and HH117 became drastically less active in the end of the experimental period as compared to the beginning of the experiment. In fact, these residents barely left the house in the last few months. The resident HH115 was more active in the middle of the experimental period as compared to the beginning and the end. The resident HH120 became less active in four months right before the last month. Finally, it appears that the rest of the residents kept similar routines during the experimental period.

Fig. 11 illustrates the monthly BRE events which are classified with $t_1 = 20$, $t_2 = 20$, and $t_3 = 30$ parameters. From the density map, we can realize that most of the residents

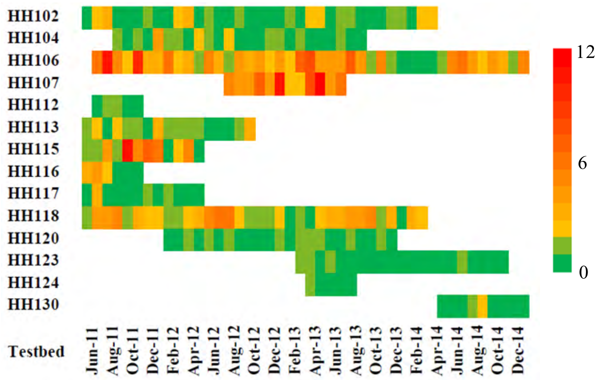

FIGURE 11. Monthly BRE event shown on a density map where BRE events are classified with $t_1 = 20$, $t_2 = 20$, and $t_3 = 30$.

made small number of BRE events, except residents HH106, HH107, HH115, and HH118. The residents HH112, HH120, and HH124, made, respectively, only two, eight, and four BRE events that occurred once in a month, and HH124 has only one BRE event in the first month of the experimental period. Moreover, the resident HH102 tends to have more BRE events mostly in spring and summer.

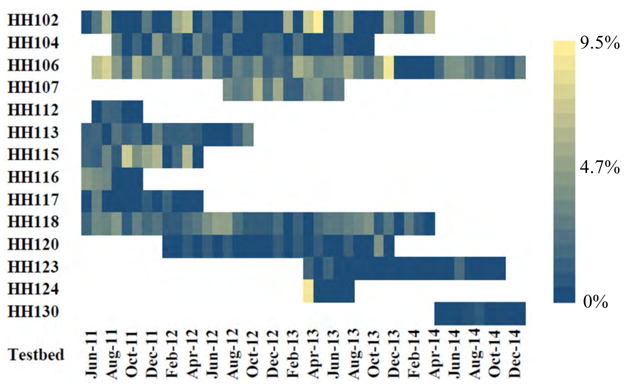

FIGURE 12. BRE percentage per month shown on a density map where BRE events are classified with $t_1 = 20$, $t_2 = 20$, and $t_3 = 30$.

Fig. 12 illustrates the monthly BRE percentage which is calculated by (1). The resident HH102 has the highest monthly BRE percentage value (9.52%), being followed by HH106 and HH124 among the fourteen testbeds. However, in terms of the average BRE percentage per month, residents HH107, HH106, and HH115 have the highest numbers of 3.26%, 3.07%, and 3.13%, respectively.

The mean values, calculated by (2), of monthly exits, monthly BRE events, and monthly BRE percentages illustrated in Figs. 10-12 are ranked in Fig. 13. The highest value (14) and the lowest value (1) stand in the first place and the last place, respectively.

The resident HH107 is ranked in the first place for all three categories indicating he/she was the most active person, who made the highest number of BRE events and BRE percentage. The residents HH115 and HH106 are the next residents who

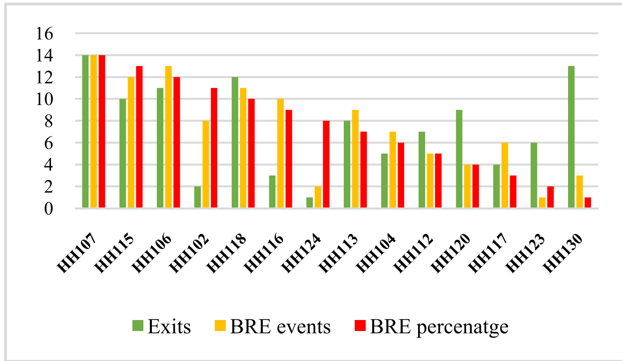

FIGURE 13. A ranking chart of average monthly exits, BRE events, and BRE percentage. the highest value (14) refers the first place in the ranking.

have the highest average BRE percentage per month, and are ranked in the first four places in terms of monthly exits and monthly BRE events. HH102 is ranked in the fourth place in the BRE percentage category. Notably, HH102 is ranked in the second place from the last in the category of the average monthly exits. This result reveals that the residents made a high number of BRE events even they were less active. On the contrary, the resident HH130 is ranked in the second place in terms of the average monthly exits, but he/she is ranked in the bottom in terms of the average monthly BRE percentage.

For all testbeds, correlation coefficients between average monthly exits and BRE events, average monthly exits and BRE percentage, and average monthly BRE events and BRE percentage are calculated as 0.66, 0.25, and 0.85, respectively. Thus, all three variables have a positive correlation between each other, but the number of exits and BRE percentage are weakly correlated.

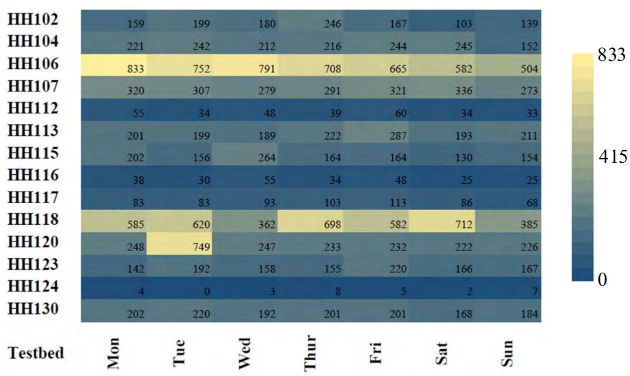

FIGURE 14. Weekday's exit events shown on a density map.

B. WEEKDAY'S EXITS, BRE EVENTS, AND BRE PERCENTAGE

Fig. 14 shows the weekday's events where the highest exit value (833) and the lowest exit value are represented by yellow and dark blue, respectively. From the density map, we can observe that the residents HH106 and HH118 were the most active residents. Residents HH107, HH130, and HH104 have the lowest coefficient of variances (CV) that are 7.8%, 8.4%,

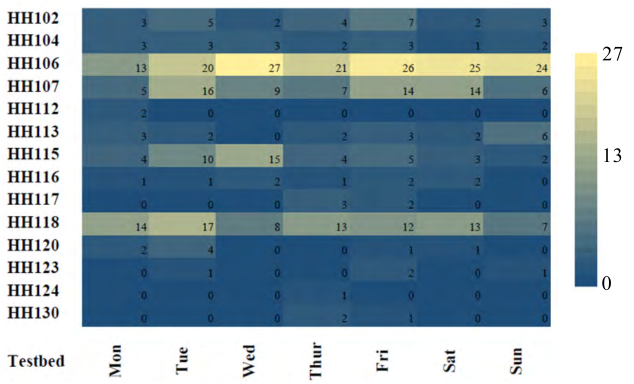

FIGURE 15. Weekday's BRE event shown on a density map. BRE events are classified with $t_1 = 20$, $t_2 = 20$, and $t_3 = 30$.

and 14.9%, respectively. Therefore, they are the residents who have the most constant number of exits in a whole week. Furthermore, we can observe that generally Sunday is the least active day, and Tuesday is the most active day.

Fig. 15 illustrates the weekday's BRE events that are classified with $t_1 = 20$, $t_2 = 20$, and $t_3 = 30$. The density map indicates that most of the residents made small number of BRE events, except residents HH106, HH107, HH115, and HH118. Most of the BRE events occurred during Tuesday to Saturday. For the resident HH106, the number of BRE events increased during Monday to Sunday.

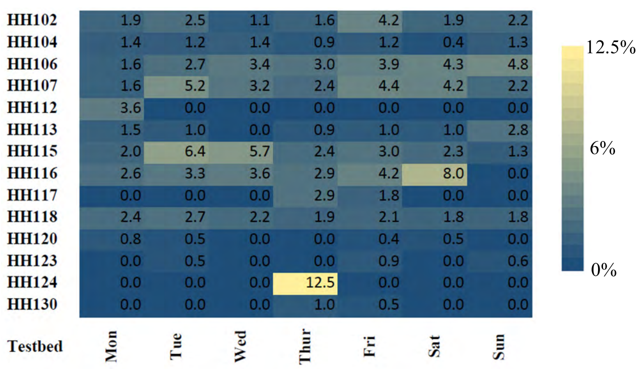

FIGURE 16. BRE percentage per weekday as a density map. BRE events are classified with $t_1 = 20$, $t_2 = 20$, and $t_3 = 30$.

Fig. 16 illustrates BRE percentage per weekday ($t_1 = 20$, $t_2 = 20$, and $t_3 = 30$) on a density map. The highest BRE percentage value is 12.5% on Thursday of the testbed HH124. From the density map, we could implicate that residents HH107, HH115, and HH116 have high BRE percentages during Tuesday to Saturday. The resident HH116 made BRE events on all weekdays except on Sunday. Moreover, the resident HH118 has the least CV (16.2 %), indicating the resident has constant BRE percentages on weekdays.

C. VALIDATION OF THE ALGORITHM

We have checked the performance of the algorithm according to the method described in the previous section. To validate the algorithm, we have checked all 115 BRE events of all testbeds that were classified with $t_1 = 2$, $t_2 = 2$, and $t_3 = 30$ (see Table III). The result shows that all 115 BRE events were correct (true positives); thus the accuracy of the algorithm for BRE event detection is 100%.

V. DISCUSSIONS

From Figs. 7-9, we can implicate that $t_1 = 15$, $t_2 = 15$, and $t_3 = 30$ are perhaps a good choice for the BRE event classification since most of the BRE events occurred within these intervals.

For the forget event detection, there exist two possibilities behind the BRE events, i.e., true forget event, or normal activity. We cannot validate forget events with the datasets which don't have any annotation about forget events. True forget events can be validated by inquiring the residents upon every BRE events; therefore, the BRE event detection is the first step for detecting forget events.

In addition, a large number (>30 min) of t_3, and too small numbers (<5 min) for t_1, and t_2 may not detect most of the true forget events. On the other hand, large numbers (>15 min) for t_1, and t_2 may result in high false positives. Thus, adaptive machine learning models with context aware features such as activity type, date, time, and so on, during BRE events can be very useful for the accuracy of forget event detection.

VI. CONCLUSIONS AND FUTURE WORKS

This paper has proposed a novel front-door events classification algorithm for detecting forget event of elderly people living in smart houses. The algorithm has been manually validated on all BRE events (at $t_1 = 2$, $t_2 = 2$, and $t_3 = 30$) of all fourteen open datasets that are collected by the wireless binary sensors in testbeds. Front-door events of the fourteen elderly residents are classified and analyzed in terms of total exits per month/weekday, BRE events per month/weekday, and BRE percentage per month/weekday.

With our best knowledge, this would be the first work exploring the BRE event. In addition, the relationships of BRE events and t_i parameters and appropriate values for t_i parameters that could detect most of the BRE events are investigated. Correlation coefficients reveal that the number of exits, BRE events, and BRE percentage are all positively correlated between each other. Moreover, the correlation between BRE events and BRE percentage is high (0.85), but the correlation between the number of exits and BRE percentage is weak (0.25). Thus, we think the proposed method can be a useful tool for the forget event detection.

Our next step is to conduct real-life long-term experiments with people with dementia to assess the forget event detection using adaptive machine learning scheme.

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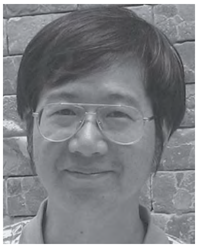

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