Deep convolutional neural network classifier for travel patterns using binary sensors

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Device-free Non-invasive Front-door Event Classification Algorithm for Forget Event Detection Using Binary Sensors in the Smart House

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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. One of the early symptoms of dementia is forgetting something when the person leaves the house. In this study, we introduce a novel front-door events (exit, enter, visitor, other, and brief-return-and-exit (BRE)) and their classification scheme that validated by using open datasets (n = 10) collected from ten single-resident testbeds by anonymous binary sensors. BRE events occur when four consecutive events (exit-enter-exit-enter) happen in some 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 years and over) during the experimental period ($\mu = 583.1 \pm 297.3$ days). The algorithm automatically classifies the resident's front-door events and ignores visitor's entrance and exit events. The experimental results reveal the significance of the t_i parameters for the number of BRE events. Since BRE events may include forget events, the proposed algorithm could be a useful tool for the forget event detection.

***Keywords*— Binary sensors, device-free, front-door events, forget event detection, non-invasive**

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., 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 in 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, for it can increase the possibility of prolonging an independent life for elderly people.

One of the earliest dementia symptom is memory lapses. For example, the person mislays an item, or leaves the lights on, or struggles to remember why he/she entered a certain room [6], or forgets something (e.g., a phone, a wallet) when he/she leaves a home. To our best knowledge, we haven't found any work in the literature 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., PIR sensors, 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 it is uncomfortable when wearing it. [18]. Therefore, device-free non-invasive systems are probably the most preferable for a long-term monitoring application.

For the time being, device-free non-invasive dementia detection is 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 forget event detection purpose.

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

- We introduce a brief-return-and-exit event as a new measure for the non-invasive forget event detection, however further research is needed for the validation of forget event detection;
- We propose front-door events classification algorithm as the first step for the forget event detection;
- For the first time, we extract front-door events from open dataset collected by device-free non-invasive binary sensors in a long-term.

III. PROPOSED METHOD

Fig. 1 illustrates a block diagram of the proposed scheme of detecting the front-door events with a brief-return-and-exit (BRE) percentage analysis using raw data collected from non-invasive binary sensors.

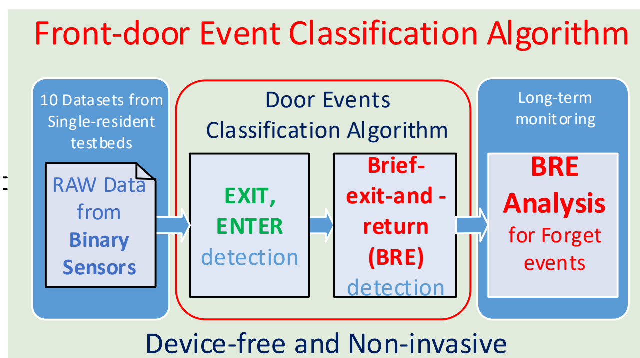

Fig. 1. Block diagram of the front-door events detection and trend analysis.

A. Testbeds, Binary Sensors, and Datasets

Ten testbeds (HH102, HH104, HH107, HH113, HH115, HH116, HH117, HH118, HH120, and HH123) out of 25 "Horizon House" testbeds from Washington State University's Center for Advanced Studies in Adaptive Systems (CASAS) project [19] 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 offer 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. We don't know each resident's exact age, sex, cognitive state, activity level, etc. Each testbed, equipped with more than 20 binary sensors [20], has a kitchen, a dining area, and at least one bathroom and one bedroom.

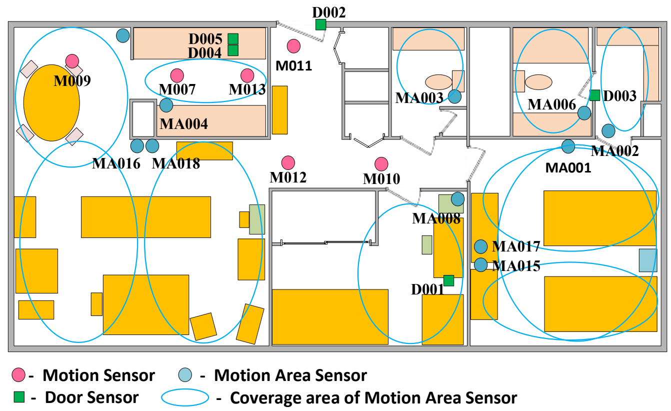

Fig. 2. Layout of the HH118 testbed in CASAS project.

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 passive infrared sensor that is fixed on the ceiling, sensing movements under it. MA0XX is a passive infrared sensor which senses movements within the coverage area shown by a blue oval in the figure, and D00X is a magnetic sensor to sense whether the door is open or not.

The datasets were collected during 2011-2014, with different experimental periods (μ = 583.1 ± 297.3 days), and number of events (μ = 3.38 ± 2.52 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 MA015 through the location of M012, and then opened the door, finally closing the door. But this event can't make sure whether resident was still inside or went out of the house.

Date	Time	Sensor	Status
2011-11-04	09:40:23.708148	MA015	ON
2011-11-04	09:40:24.104128	M012	ON
2011-11-04	09:40:24.302148	MA015	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

Fig. 2. Typical samples of raw data.

B. Front-Door Events

We define five types of the front-door events for the residents who live alone. Table 1 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", and ends with "OPEN". ENTER event starts with "(No M)", because there won't 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 man) come and go, sequences are same as in EXIT event except the last one. Thus the algorithm needs to wait the fourth sequence to make sure the event was VISITOR or EXIT.

TABLE I. FRONT-DOOR EVENTS AND THEIR SEQUENCES OF SENSOR LOGS

Front-door event	Sequences of sensor logs
EXIT	M→ OPEN→CLOSE →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 visitor 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 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 some time.

The last 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 events 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 forgot 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.

C. Front-door Events Classification Algorithm

Front-door events classification algorithm is illustrated in Fig. 3 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 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.

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
```

Fig. 3. Front-door events classification algorithms.

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". Then 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", *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 next enter occurs more than t_3 min after previous exit (line 6).

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 2. In the table, 20:20:30 indicates $t_1 = 20$ min, $t_2 = 20$ min, and $t_3 = 30$ min and 2:2:30 indicates $t_1 = 2$ min, $t_2 = 2$ min, and $t_3 = 30$ min.

To validate the classification algorithm, we manually checked all the door events of HH117 with the raw data of HH117 and the validation accuracy was 100%.

TABLE II. STATISTICS OF EXITS AND BRE EVENTS

Testbed	Total days	Total Exits	Exits/day	Out Time /exit [hr]	20:20:30		2:2:30	
					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
HH107	359	2127	5.92	0.50	71	5.93	26	2.17
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
HH117	348	629	1.81	0.73	5	0.43	0	0
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
μ	**583.1**	**1577.2**	**2.79**	**1.00**	**28.50**	**1.72**	**7.90**	**0.54**
σ	**297.3**	**1016.7**	**1.41**	**0.45**	**28.48**	**1.84**	**9.60**	**0.85**

The resident HH102 made a total of 1193 exits on 1039 days, and has the lowest daily exit number (1.15), and slightly smaller than the average out time per exit (0.90 hr) among the ten. The resident HH107 made the highest daily exit number (5.92), and the highest monthly BER events at both time intervals, moreover the resident has the second lowest (0.5 hr) out time per exit. Residents HH117, HH120, and HH123 are the three residents who has the lowest monthly BRE events. Figs. 4-6 represents the relationships of BRE events and t_i parameters.

Figs. 4-6 represents the relationships of BRE events and t_i parameters, we can observe that the number of classified BRE events is quite dependent on t_i parameters. As shown in the Fig. 4, 61.5%, 86.7%, and 97.3% 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. 5, similarly, 56.3%, 76.6%, and 89.3% of all BRE events (at $t_2 = 20$ min) are detected on 5 min, 10 min, and 15 min, respectively. In Fig. 6, 59.5% and 85.1% of all BRE events (at $t_3 = 0$ min) occurred within 10 min, and 30 min, respectively.

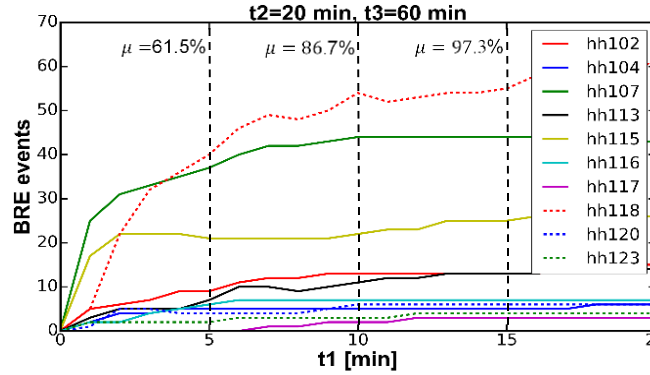

Fig. 4. BRE events vs. t_1 parameter for all testbeds.

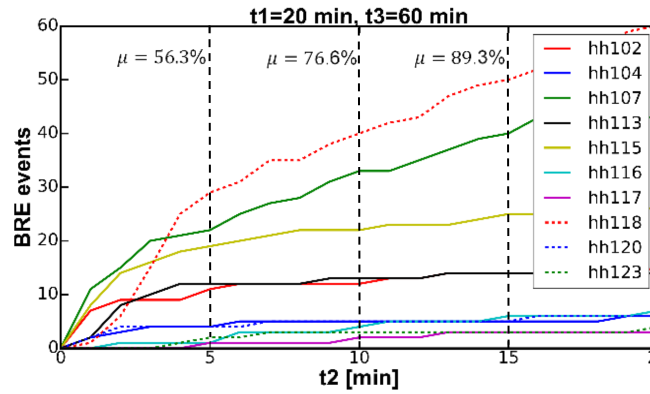

Fig. 5. BRE events vs. t_2 parameter for all testbeds.

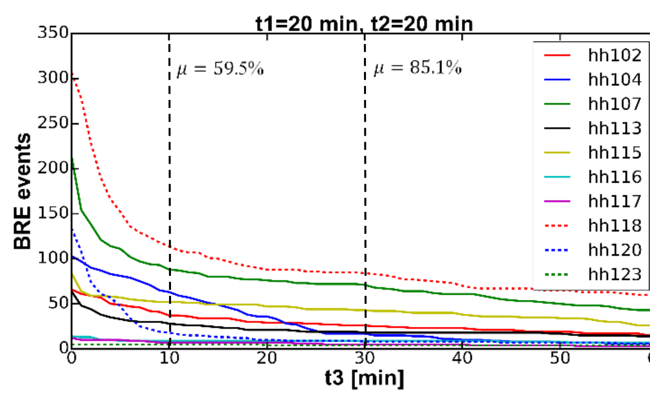

Fig. 6. BRE events vs. t_3 parameter for all testbeds.

V. DISCUSSIONS

From Figs. 4-6, 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, behind the BRE events there can be two possibilities, 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.

Moreover, 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 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

In this paper, for the first time in the literature, we proposed a novel front-door events classification algorithm for daily activity monitoring and forget event detection of elderly people living in single-resident smart houses. The algorithm is validated one of the ten open datasets that collected by the wireless binary sensors in single-resident testbeds. Front-door events of ten elderly residents are classified and analyzed in terms of total exits per month, BRE events.

BRE events and t_i parameters are introduced for forget event detection. Appropriate values for t_i parameters that would detect most of the BRE events are introduced. In conclusion, we think our proposed method can be a useful tool for the forget event detection.

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

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