Frailty Detection using Presence in a Room

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Abstract

The elderly population is steadily increasing in most countries due to a decline in birth and mortality rate. The population of senior citizens living independently has also become significant. This has led to an active research focus in geriatric wellness.

One of the common effects of ageing is Frailty which is seen in the Elderly population. This research is focused on detecting activities specific to frailty in typical natural home environment of the geriatric population living alone. To this end, we evaluated only Passive Infra-Red (PIR)-based motion and magnetic door contact sensors for detection of frailty through a unique combination of custom and statistical techniques to achieve reasonable accuracy. This is further validated using ground truth obtained through surveys to understand the level of frailty of selected elderly people.
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Keywords

Elderly, Frailty, Passive Infrared Sensors, Algorithm, Median, Unobtrusive, Supervised Learning

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1. Introduction

In many countries, there is a significant rise in the number of senior citizens living independently. As a result, there is an active research focus in the wellness and care of the geriatric population. In this research, we focus on frailty, which is defined as a "clinical syndrome in which three or more of the following criteria were present: unintentional weight loss (10 lbs in past year), self-reported exhaustion, weakness (grip strength), slow walking speed, and low physical activity [2]". In the following sections, we describe our approach in understanding the symptoms of frailty with the right processing techniques so that the right intervention can be applied to the individual.

2. Data Description

Through the Smart Homes and Intelligent Neighbors to Enable Seniors (SHINESeniors) [1] initiative, over 90 homes of elderly living alone in Singapore have been instrumented with non-intrusive and privacy-preserving sensors. Each home is equipped with at least 4 PIR motion sensors, one in each room. Each PIR sensor detects motion by sensing the change in temperature between the room and a body temperature. In addition, a door contact sensor is mounted at the main entrance of the dwelling. Finally, each elderly is also given a help button on a lanyard, which they can activate in case they need help. All sensors communicate with backend cloud servers through a home-based gateway transmitting data over a 3G data network. Figure 1 shows the layout of the sensor-based monitoring system.

This study utilizes sensor data collected over two time periods: (i) between November 2017 and July 2018 (**Baseline**) and (ii) between August 2018 and March 2019 (**Follow-up**). In addition, it utilizes survey data obtained from two surveys conducted on the elderly: baseline in March 2018 and follow-up in December 2018. The survey data includes information about their demographics, mental health, physical health and psychosocial well-being, and serve as ground truth validation for the sensor-based frailty algorithm. The objective of selecting this specific dataset is due to the flexibility in analyzing the sensor data and validating with multiple survey that include baseline and follow-up and interacting with Elderly and caregivers. This is not something that will be available to us if we gone with public datasets.

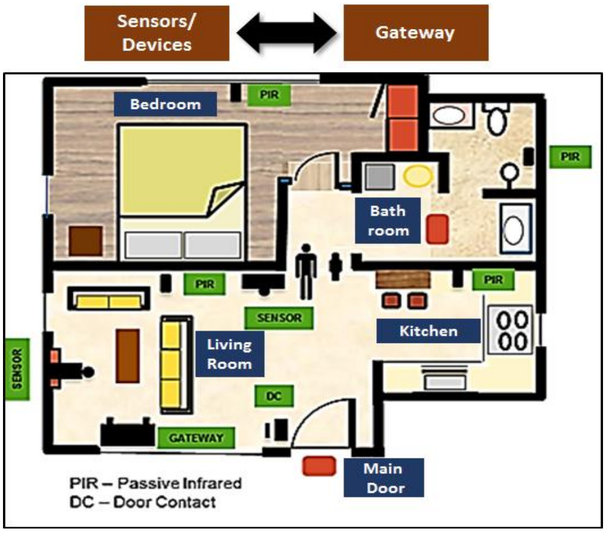

Figure 1: Sensor-based monitoring system and sensor data

3. Sensor based Frailty Detection

In an earlier related work [3], the authors examined the possibility of using the in-home sensor-based monitoring system to detect frailty in 46 participants of the SHINESeniors project. Baseline and follow-up surveys were conducted in March 2016 and March 2017, and sensor data 30 days prior to the survey date were used for frailty detection.

Motivated by promising results from the above study, this follow-up study proposes a Sensor-based Frailty algorithm based on data (both sensor and survey) obtained in a later time period (i.e., November 2017 to March 2019). We first describe the algorithmic approach (illustrated in Figure 2) to understand Frailty in the elderly based on sensor data. Specifically, we aim to detect the symptoms of Frailty based on the following daily living patterns of the elderly.

- Movement within the home (i.e., number of transitions from room to room)

- Time spent in bedroom during the daytime (i.e., **between 0600 to 1800)**
- Number of outings (i.e., number of door contact events)

The intuition for using only the above three patterns will certainly help in determining the effective movement of the elderly within and outside the home. Plus, given only the availability PIR and Door sensor data we can only able to determine the above three movement patterns effectively.

The notations used in the Sensor-based Frailty algorithm is listed in Table 1. Each step of the algorithm is described in the following.

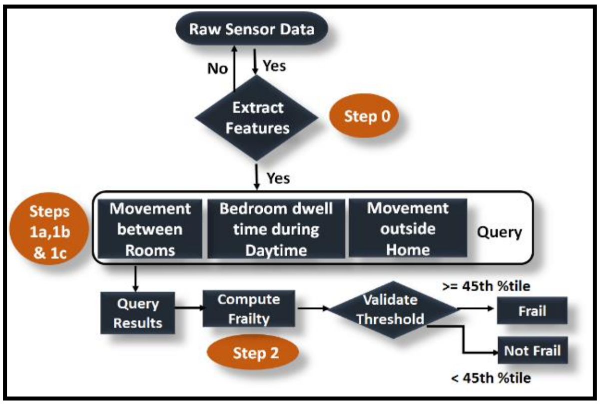

Figure 2: Sensor-based Frailty Detection Algorithm

Table 1

Notations used in Sensor-based Frailty Algorithm

Notation	Meaning
D_{sf}	Sensor Feature Dataset
D_{drc}	Subset of feature dataset corresponding to daily room change
D_{dbd}	Subset of feature dataset corresponding to daily bedroom duration in daytime
D_{ddc}	Subset of feature dataset corresponding to daily door contact events
i_{drc}	Indices of sensor feature dataset entries corresponding to daily room changes
i_{dbd}	Indices of sensor feature dataset entries corresponding to daily bedroom duration in daytime
i_{ddc}	Indices of sensor feature dataset entries corresponding to daily door contact events
p_{drc}	Percentage of days with reduced room change
p_{dbd}	Percentage of days with increased bedroom duration in daytime
p_{ddc}	Percentage of days with reduced door contact events
p_f	Frailty percentage computed from sensor feature dataset
MED(D)	Function to return median average
COUNT(D)	Function to return the size of dataset D
QUERY(D, "x ")	Function to query the dataset D and return subset that satisfies condition x

Step 0 – Extract Features

The Featured Sensor Dataset basically takes the raw sensor input and create as many features as possible so that it makes the dataset very detailed and clear. The clarity in coming up with featured dataset will itself reveal the data patterns in more simplistic way and we can have options to mine the dataset.

Table 2

Raw Sensor Dataset

elderlyid	sensor_id	location	observationTimeStamp
Elderly1	6004-m-01	living_oom	2017-11-01T00:01:34
Elderly1	6004-d-01	door	2017-11-01T00:01:42
Elderly1	6004-d-01	door	2017-11-01T00:18:51
Elderly1	6004-m-01	bedroom	2017-11-01T00:18:52

The original raw dataset of sensor approximately comes with Sensor ID, Sensor datetime and sensor location (refer Table-2) , then an algorithm on top of this raw sensor data which will first create a Featured Sensor dataset in time series.

The featured dataset will include but not limited to Observationtimestamp, elderlyid, Date, Hour, Minute, Second, Day, Week, Month, Year, Weeday/Weekend, FromLocation, Tolocation, Timespent, RoomChangeIndicator, "Daytime (Y/N)", "Timeperiod" i.e. whether it is morning 6.00 am to 9.00 pm or Afternoon 3.00 pm to 6.00 pm etc.

Every row in raw sensor data will convert from the above data structure. For example, If the raw sensor data has 1000 rows for 3 months as an example, this will have 3 months of enriched features. Few key fields of a sample Featured Dataset is given in Table 3

The objective of this step is to extract useful features from time-stamped motion sensor and door contact sensor readings that are relevant to frailty based on the raw sensor data. Table 3 provides a sample sensor feature dataset that illustrates the movement of elderly1 from location to location, the duration in each location, as well as the time period for which the transition/sojourn happens.

Table 3
Sample of Sensor Feature Dataset (Elderly1)

Observation timestamp	Elderly_ID	Daytime	From Location	ToLocation	Room Change Ind	Time Spent	Time Period
4/1/2018 1:05	Elderly1	N	door	livingroom	Y	3	E9to6
4/1/2018 1:23	Elderly1	N	livingroom	bedroom	Y	5	E9to6
4/1/2018 1:23	Elderly1	N	bedroom	bedroom	N	1091	E9to6
4/1/2018 1:24	Elderly1	N	bedroom	kitchen	Y	8	E9to6
4/1/2018 1:24	Elderly1	N	Kitchen	bathroom	Y	5	E9to6

Step 1a – Calculate movement between rooms

Based on the *RoomChangeInd* feature, we can extract the daily total room changes over the duration of the dataset. By extracting a subset comprising days for which the daily total is below the median, we can determine the percentage of days for which the elderly experienced reduced daily room changes as an indication of frailty. This is illustrated as follows:

i_{drc} = QUERY(D_{sf}, “RoomChangeInd = Y & group by Date”)
$D_{drc} = D_{sf}\{i_{drc}\}$
i_{rdrc}= QUERY(D_{drc} ,“$D_{drc} < MED(D_{drc})$”)
$p_{rdrc} = (|D_{drc}\{ i_{rdrc} \}| / |D_{drc}|) * 100$

The introduction of percentage in all the steps (1a, 1b and 1c) helped us in determination of quantitative change in terms of Movement between Rooms (Step 1a) , Calculate Bedroom dwell time (Step 1b) and Movement outside Home (Step 1c).

Step 1b – Calculate Bedroom dwell time during Daytime

Based on the RoomChangeInd, FromLocation, ToLocation and TimePeriod features, we can extract the daily bedroom duration in the daytime. By extracting a subset comprising days for which the daily duration is above the median, we can determine the percentage of days for which the elderly experienced increased daily bedroom duration as an indication of frailty. This is illustrated as follows:

i_{dbd}= QUERY($\mathbf{D}_{sf}$,“RoomChangeInd = N, FromLocation = bedroom, ToLocation=bedroom, TimePeriod=["M6to9","M9to12","A12to3","E3to6"] & group by Date”)
$\mathbf{D}_{dbd} = \mathbf{D}_{sf}\{ i_{dbd} \}$
i_{idbd} = QUERY($\mathbf{D}_{dbd}$,“$\mathbf{D}_{dbd} > MED(\mathbf{D}_{dbd})$”)
$p_{idbd} = (|\mathbf{D}_{dbd}\{ i_{idbd} \}| / |\mathbf{D}_{dbd}|) * 100$

Step 1c – Calculate Movement outside Home

Based on the *ToLocation* feature, we can extract the daily total door event (i.e., daily outings) over the duration of the dataset. By extracting a subset comprising days for which the daily total is below the median, we can determine the percentage of days for which the elderly experienced reduced daily door counts (i.e., reduced outings) as an indication of frailty. This is illustrated as follows:

i_{ddc}=QUERY(“ToLocation=Door & group by Date”)
$\mathbf{D}_{ddc} = \mathbf{D}_{sf}\{i_{ddc}\}$
i_{rddc} = QUERY($\mathbf{D}_{ddc}$,“$\mathbf{D}_{ddc} < MED(\mathbf{D}_{ddc})$”)
$p_{rddc} = (|\mathbf{D}_{ddc}\{ i_{rddc} \}| / |\mathbf{D}_{ddc}|) * 100$

Step 2 – Compute Frailty

This is the final step in fundamentally determining frailty of the elderly. Here, we assign weightage to each of the previous steps to give more specific preference to certain processes based on the domain understanding of the environment as follows:

- Step 1a - Movement between Rooms - 50%
- Step 1b – Stay in Bedroom during Daytime – 30%
- Step 1c – Movement outside Home – 20%

Accordingly, we compute the Frailty Percentage as follows:

$$p_f = p_{rdrc}*0.5 + p_{idbd}*0.3 + p_{rdc}*0.2$$

Some key advantages of the proposed algorithm are:

- The algorithm uses only sensor data which is considered unobtrusive rather using other methods like wearable devices.
- The algorithm does not require any individual health information as it uses only sensor data,
- The algorithm does not need a labelled dataset unlike supervised machine learning,
- The algorithm understands frailty through statistical and custom formula which can be easily fine-tuned for optimization,
- Finally, the algorithm bases its findings from a featured dataset that is derived from the raw sensor data.

For ground truth validation of the sensor-based frailty detection algorithm, we used up to 38 deficits to compute the frailty index in this study as a higher number of deficits used has been shown to yield better results.

4. Results

In this section, we present some results obtained for the proposed sensor-based frailty detection algorithm for the period (i) November 2017 and July 2018 (**Baseline**) and (ii) between August 2018 and March 2019 (**Follow-up**).

Among the SHINESeniors participants, 65 residents participated in the baseline survey, and 47 participated in the follow-up survey. As the profile of the residents who participated in the surveys are different, we selected 39 residents with similar demographics. Out of these 39 participants, those with insufficient sensor data for the 2 periods, or who did not participate in both surveys, were removed, resulting in 11 residents (elderlies) for this study.

Table 4
Frailty percentage / indices

Resident	pf,baseline	pf,followup	FI baseline	FI followup
Elderly1	48	44	0.315	0.342
Elderly2	46	45	0.27	0.189
Elderly3	45	48	0.171	0.142
Elderly4	42	48	0.108	0.135
Elderly5	43	44	0.105	0.21
Elderly6	42	44	0.027	0.054
Elderly7	45	44	0.157	0.21
Elderly8	47	48	0.105	0.105
Elderly9	46	47	0.027	0.056
Elderly10	44	43	0.078	0.052
Elderly11	46	48	0.162	0.189
45^{th} %tile	45	44.5	0.1065	0.1385

4.1 Frailty Classification

According to an epidemiology study in Singapore [4], the prevalence of pre-frailty and frailty among the elderly aged 65 years and older in Singapore stands at approximately 6.2% and 37% respectively. Accordingly, we use the 45^{th} percentile split at each time period, both for the frailty percentage and frailty index, to divide the elderly into two groups: robust and frail. The corresponding 45^{th} percentile values are provided in Table 4. Accordingly, the frailty classification is given in Table 5.

Table 5
Frailty classification

Resident	pf, baseline	pf, followup	FI baseline	FI follow-up
Elderly1	Frail	Not frail	Frail	Frail
Elderly2	Frail	Frail	Frail	Frail
Elderly3	Frail	Frail	Frail	Frail
Elderly4	Not frail	Frail	Frail	Not frail
Elderly5	Not frail	Not frail	Not frail	Frail
Elderly6	Not frail	Not frail	Not frail	Not frail
Elderly7	Frail	Not frail	Frail	Frail
Elderly8	Frail	Frail	Not frail	Not frail
Elderly9	Frail	Frail	Not frail	Not frail
Elderly10	Not frail	Not frail	Not frail	Not frail
Elderly11	Frail	Frail	Frail	Frail

From Table 5, it is observed that the Sensor-based Frailty classification matches the Survey-based Frailty classification for 13 out of 22 instances, achieving an accuracy of 59%.

To provide further insights into the results, we perform case studies on two participants (Elderly 3 & Elderly 1) by investigating their frailty percentage and component scores, frailty index, and other anecdotal information obtained from the study. The latter includes history of help request activation, fall history, employment information etc. Specifically, we plot $\mathbf{D}_{\mathrm{drc}}$, $\mathbf{D}_{\mathrm{dbd}}$ and $\mathbf{D}_{\mathrm{ddc}}$ for these elderlies over the baseline duration in Figure 3 & 4 respectively.

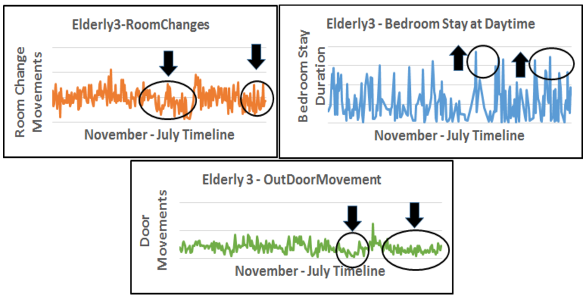

Figure 3: Select activity patterns of Elderly 3

From Figure 4, we can observe a reduction in daily room movement door events plus increase in bedroom stay during daytime, which are indicative signs of frailty. In fact, Elderly 3 experienced a fall and had just returned home from nursing care in early December 2017. Moreover, Elderly 3 requested for help through the help button several times due to reduced movement during this period. These observations corroborate with Elderly 3 being classified as frail based on the frailty percentage (sensor data) as well as the frailty index (survey data).

To further substantiate the help button correlation with frailty, we examined another elderly, Elderly 1, who also activated the help button a few times seeking help. Based on the sensor data analysis of Elderly 1 in Figure 4, we also observe a reduction in daily room movement stay and door events, along with few increments on change in bedroom duration. Again, these observations corroborate with Elderly 1 being classified as frail.

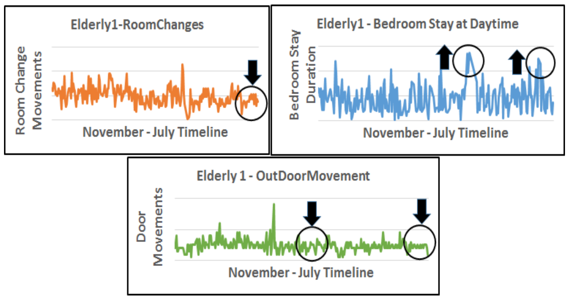

Figure 4: Select activity patterns of Elderly 1

4.2 Frailty Change (Baseline vs Follow-up)

According to the Sensor-based Frailty Detection algorithm, the frailty percentage increased for 7 elderlies (became more frail) and decreased for 4 elderlies (became less frail). Based on the survey, the frailty index increased for 7 elderlies (became more frail), decreased for 3 elderlies (became less frail) and remained unchanged for 1 elderly. The frailty change according to the survey is plotted in Figure 5.

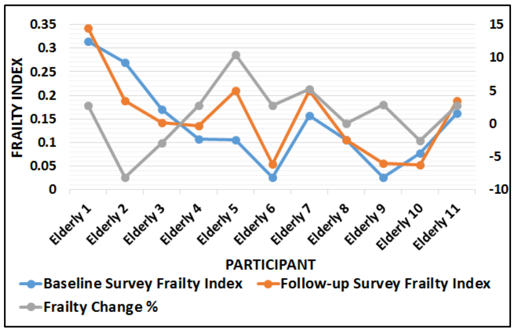

Figure 5. Frailty Change in Elderly (Baseline to Follow-up Survey)

Among the 7 elderlies detected to be more frail based on sensor data, 5 of them were also deemed as more frail according to the survey. Among the 4 elderlies detected to be less frail based on sensor data, 2 of them were also deemed as less frail based on the survey. This corresponds to a frailty change detection accuracy of 63%. This suggests that sensor-based frailty detection may be more accurate in detecting frailty change over time as compared to frailty classification.

5. Conclusion

In this paper, we demonstrated the feasibility of using in-home unobtrusive sensors to autonomously detect frail or pre-frail elderly as well as detect frailty change in the elderly over time for community dwelling elderly living alone. Based on motion sensors installed in each room of the apartment and one door contact sensor on the main door, we proposed a frailty detection algorithm based on movement between rooms, duration in bedroom in the daytime, as well as door event counts. These behavioral aspects of the elderly have been shown in a previous study to be useful in discriminating frail / pre-frail elderly from robust elderly. This sensor-based frailty algorithm is validated by frailty indices computed based on deficit accumulation [5] from surveys.

Using surveys conducted in March 2018 (baseline) and December 2018 (follow-up) and sensor data from November 2017 to July 2018 (baseline) and August 2018 to March 2019 (follow-up) from 11 elderlies, we achieved frailty classification accuracy and frailty change detection accuracy of 59% and 63% respectively. The 11 elderlies were split into two groups: frail and non-frail using a 45th percentile split, based on actual prevalence of frailty from an epidemiology study conducted in Singapore.

6. References

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