



**HAL**  
open science

## Detecting change in the routine of the elderly

Soumaya Msaad, Yannick Wend Kuni Zoetgnandé, Jean-Louis Dillenseger,  
Guy Carrault

► **To cite this version:**

Soumaya Msaad, Yannick Wend Kuni Zoetgnandé, Jean-Louis Dillenseger, Guy Carrault. Detecting change in the routine of the elderly. Measurement: Sensors, 2022, 24, pp.100418. 10.1016/j.measen.2022.100418 . hal-03770098

**HAL Id: hal-03770098**

**<https://hal.science/hal-03770098v1>**

Submitted on 6 Sep 2022

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# Detecting change in the routine of the elderly

Soumaya Msaad<sup>a</sup>, Yannick Wend Kuni Zoetgnande<sup>a</sup>, Jean-Louis Dillenseger<sup>a</sup> and Guy Carrault<sup>a,\*</sup>

<sup>a</sup>Univ Rennes, Inserm, LTSI - UMR 1099, F-35000 Rennes, France

## ARTICLE INFO

### Keywords:

Elderly  
Routine  
Frailty  
Depth sensor  
Deep learning  
Machine learning  
Minimum Edit Distance

## ABSTRACT

Recent studies shown that elderly persons have a well-defined, regular life routine, organized around their postures, habits, environment, and social relations. Monitoring the daily routine will allow to detect person behavior changes. In this paper, we propose two solutions for detecting changes in the elderly person behavior based on the daily living activities monitoring. For both proposed methods, the person's activity is recorded with a depth sensor to preserve his anonymity. In a first step, the recorded images are classified according to the posture of the person (sitting, standing, lying down, absent and fall) by a modified ResNet-18 model. The first method is a binary decision problem and consists in classifying routine and non routine day according to the postures. Then a behavior index is built using the output of the classifier. The second method consists in describing the routine day by the temporal succession in postures. A similarity between the recorded day and the routine day postures is computed using the minimum edit distance which acts as a behavior index. The number of transformations reflects the change in the person's behavior. Both methods have been tested on a database of depth images recorded in a nursing home over a 85 days period. Inferring the whole dataset gives an accuracy of 89.09% and a F1-score of 85.84% for posture estimation. Using Random Forest, an accuracy of 92% was retrieved for routine/non routine day classification. The two proposed indexes proved their reliability in monitoring behavior changes. The first approach proposes a behavioral index with a median magnitude error less than 0.01 compared to the ground truth. The second one provides a significant difference in the number of transformations between the postures in routine days (Interquartile range 25th-75th=[28, 48]) and non routine days (Interquartile range 25th-75th=[55, 62]).

## 1. Introduction

The aging of the population is a global phenomenon: almost every country in the world is facing an increase in the number of seniors. This phenomenon will have an implication on almost all sectors of society. Therefore, several projects of research have proposed and implemented solutions for the well-being of the elderly. The goal of these projects is not only that the elderly people live longer but also that they live in better health, preventing disability and age-related loss of autonomy. For this, one of the major tendencies in our society is that the elderly person must live as long as possible in autonomy at home in his daily environment. This autonomy is currently made possible thanks to the implementation of health care technologies at home.

It is reported in the literature that elderly people establish life routines (a series of activities) that are repeated every day on a more or less regular basis [1]. A long term change in this routine can be a warning sign of a growing frailty [2] or a loss of autonomy [3].


Some work proposes wearable devices that detect postures (sitting, lying down and standing), falls and estimates routine activities using sensors such as accelerometers [4, 5]. However, these devices must be worn for a large part of the day, and the elderly person do not agree to wear them or may forget to wear them, for example after a shower. Other sensors can be found in smart homes and can help in identifying routine activities. Acoustic sensors [6], sensors

placed in the ground [7] and several vision based cameras traditional video [8], depth [9], thermal [10, 11], or passive infrared cameras [12], were already proposed in this way. Indeed, vision-based solutions are particularly useful in a smart homes because they are easy to implement, relatively cheap and totally passive. Their main drawback is that they are intrusive in the private life especially video cameras. In order to preserve personal privacy, we have recently developed a solution based on low-cost thermal and depth sensors [13]. In a previous work, we have already demonstrated the interest of this approach to detect a fall [14]. The objective of this paper is now to go further and to demonstrate that it is possible *i*) to establish routines from the activities and *ii*) to estimate the changes in this routine that may sign the person's health status. To do this, we explored in this paper two different approaches for detecting changes in the habits of elderly people. Section 2 describes the architecture we used for posture classification and behavior change detection. Section 3 details the experimentation framework while Section 4 presents the results. Section 5 discusses the interest of behavior change detection to understand frailty trajectories in older persons. Section 6 concludes the paper and presents some perspectives.

## 2. Methods

The proposed methods are split into 4 steps as shown on Fig. 1. A device comprising depth sensor (step 1) is placed in a room. The recorded depth images provide information on person's activities. In step 2, images are analysed and postures (sitting, standing, lying down, absences and falls) are classified using a deep neural network. For simplicity of

\*Corresponding author

 guy.carrault@univ-rennes1.fr (G. Carrault)

ORCID(s):

the presentation, we define absence of the person and falls as a posture. Monitoring of the daily routine and change detection behavior are then combined (step 3). Two indexes that will be further detailed are proposed and studied in this work (step 4).

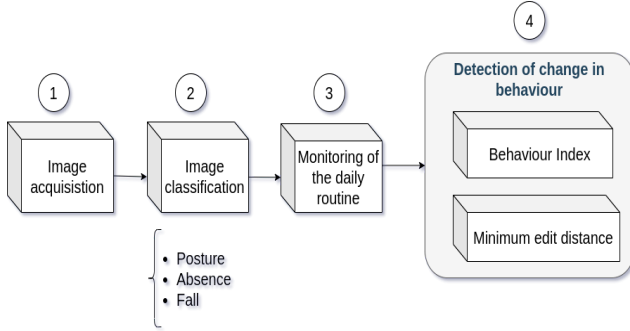


Figure 1: Proposed behavior change detection framework.

## 2.1. Image acquisition

The manufactured device is depicted in the Fig 2. The device is placed high on a ceiling in order to record images with a good viewpoint. This device consisted in calibrated depth sensors. This last one was a Kinect-like sensor (640 × 480 px @ 30 fps). Fig. 3 shows some examples of recorded depth images acquired in a real room of a retirement home or in different rooms of a real apartment.

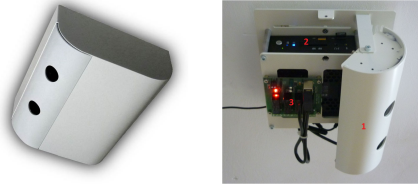


Figure 2: Devices used to acquire the databases (with the agreement of [13]).

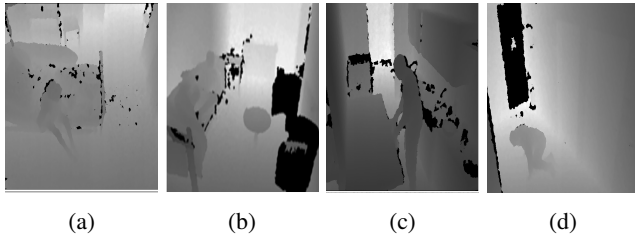


Figure 3: Several depth images examples. Person in (a): is sitting on a bed in a room of a retirement home, (b): is lying down on the bed of a room in an apartment, (c): is standing in the kitchen of an apartment, (d): falling in the hallway of an apartment.

## 2.2. Image classification

The table 1 presents some examples of the activities and postures associated to each activity.

Activities	Postures
Watching TV	Sitting
Cooking	Standing
Having a nap	Lying down
Leaving the house	Absent
Cleaning the house	Standing
Reading on the sofa	Sitting
Taking a shower	Absent
Sitting at this desk	Sitting
Sleeping	Lying down

Table 1

Example of activities and postures during the day for an elderly person.

Layer Name	Output Size	ResNet-18
<i>conv1</i>	112 × 112 × 64	7 × 7, 64, stride 2
<i>conv2<sub>x</sub></i>	56 × 56 × 64	3 × 3 max pooling, stride 2 $\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 2$
<i>conv3<sub>x</sub></i>	28 × 28 × 128	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 2$
<i>conv4<sub>x</sub></i>	14 × 14 × 256	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 2$
<i>conv5<sub>x</sub></i>	7 × 7 × 512	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 2$
average pooling	1 × 1 × 512	7 × 7 average pool
fully connected	$\kappa$	512 × $\kappa$ fully connections
softmax	$\kappa$	

Table 2

Description of ResNet-18 architecture with  $\kappa$  the number of classes used in this work.

Our main goal is to create a model that is able to determine and classify the content of a given image: the senior's absence or his posture. If such a model is efficient and fast on one image, we can use it to classify all the images of the sequence and use this temporal classification to detect changes in behavior.

Since 2012 and AlexNet [15], deep learning models have achieved outstanding results for image classification with networks as VGGNet [16], GoogleNet [17] or Residual Networks (ResNet families) [18]. We proposed to use such deep neural network for our classification purpose. Among these networks, we choose to use ResNet. The main advantage of the ResNet architectures is that they are easier to optimize and can be made more accurate by increasing the depth. The principle of ResNet architectures is that each layer learns residual functions with reference to the layer inputs instead of learning unreferenced functions. We chose ResNet-18 for a trade-off between computation time and accuracy. This network is composed of five convolutional modules as detailed in Table 2.

The input of the model will be a depth image and the output of the model is the prediction. The first module is a shallow features extractor with a learned kernel size of  $7 \times 7$ , 64 filters and a stride of 2. The other modules are some bottlenecks with  $3 \times 3$  kernels convolutional layers. The last module  $conv5_x$  is followed by an average pooling and a fully connected layer. The output of the neural network is a probability distribution over the  $\kappa$  predicted output classes.

Training such deep models from scratch can require a very large dataset and a lot of time. We used ResNet model pre-trained on the dataset provided by the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) for the evaluation of algorithms for object detection and image classification [19]. It provides RGB images but we preferred for our purpose to convert them in gray scale in order to be closer to the image characteristics of a depth camera application. In order to avoid over-fitting, we modified the model by adding a dropout of 90% before the fully connected layer. Such a strategy acts as a regularization of our model.

### 2.3. Daily routine Monitoring

Two approaches are compared in this study. The first one exploits the classifications of the deep neural network and estimates the percentage of time  $i$  in the lying down posture (%TLP),  $ii$  in a sitting posture (%TSP),  $iii$  in standing posture (%TStP),  $iv$  absent (%TAD) and the number of falls (NF) and builds a new daily routine index gathering all these information. It is worthwhile to mention that the issue of the fall must be carefully considered and in any case each detected fall leads to an alarm. Nevertheless, the number of falls is considered as one of the indices of the routine and can explain the behavior of the person. So, a sudden increase in the number of falls per day would be considered as an abrupt change in routine. For some frail elderly people, falls are quite frequent [20, 21] and are therefore part of their daily routine. This is for example the case for the elderly person observed in the proposed experiment. Moreover, the detection of the numbers of falls allows to understand the causes (congestion in a space of the habitat, steps of the stairs...) and the consequences of the fall (the moment of the fall, the place, and the duration on the ground). The second one constructs a temporal sequences of the successive postures during the day and then computes a minimum edit distance (MED) from the routine day. Both are based on the assumption that the person follows a well-defined daily routine in space, time, and social relationships [1, 22]. A routine day can be defined in two ways:

1. By asking the elderly person to describe his day, then by translating the succession of activities into a succession of postures with indication of the person absence from his living space.
2. By recording the person over several days and the routine day posture at a time  $t$  corresponds to the most frequent posture over the recording period.

#### 2.3.1. Behavior Index

A day is considered regular if it describes the person's routine day, and abnormal if the person is out of their routine. The classification of the day (routine/non routine) can be seen as binary decision problem based on the computed parameters (%TLP, %TSP, %TStP, %TAD and NF). Three machine learning approaches were compared: Binary Regression Logistic (BRL), Decision Tree (DT), Random Forest (RF). We propose BRL because the classification problem is reduced to a binary classification problem; DT because it provides simple and interpretable decision rules and RF is recognized as robust while it performs learning on multiple decision trees from a different subset of the data. The performance measures were evaluated in a classical way by computing the accuracy, specificity and sensitivity of each method [23]. Therefore, the monitoring of the evolution of the daily routine over a long period of time is computed with the following Behavior Index ( $BI_n$ ):

$$BI_n = BI_{n-1} + \frac{D_n - D_{n-P}}{P} \quad (1)$$

Where  $BI_n$  corresponds to the recursive estimation of the average routine day over the period  $P$  and  $D_n = 1$  if it follows the person's daily routine and  $D_n = 0$  if it does not.

#### 2.3.2. Minimum Edit Distance Index

The MED computes the minimum number of transformations to switch from a recorded day to the daily routine. As a brief reminder, minimum edit distance is inspired from the Levenshtein distance. The MED measures the similarity between two sequences that can vary over time by associating each element of each sequence to at least one element of the other sequence by minimizing the association costs [24, 25]. The cost of an association is the distance between the two elements.

As an example, Fig. 4 shows computation of the distance between each position of a routine day {Lying, Sitting, Standing, Absence, Standing} and a recorded day {Lying, Fall, Sitting, Standing, Lying}. In grey is colored the optimal path to align the two sequences. The distance between routine day and the recorded one is reported on the right up corner and conducts to 3 transformations. They are  $i$ ) exchange Lying by Standing,  $ii$ ) insert Absence,  $iii$ ) delete Fall.

Standing	4	4	4	3	3
Absent	3	3	3	2	2
Standing	2	2	2	1	2
Sitting	1	1	1	2	3
Lying	0	1	2	3	4
	Lying	Fall	Sitting	Standing	Lying

Figure 4: Example of the number of transformations using the MED algorithm to switch from a recorded day to a routine day.

Postures	Person1	Person2	Person3	Person4
lying	39	23	92	85
sitting	155	115	310	207
fall	123	114	176	222
standing	399	249	355	529
absent	189	168	381	244

**Table 3**  
Distribution of the number of images per person in the dataset SYMH.

Postures	Bedroom	Kitchen	Entrance	Living room	Bathroom
lying	132	0	0	107	0
sitting	209	0	0	578	0
fall	191	48	173	81	142
standing	137	211	205	720	259
absent	86	180	163	277	276

**Table 4**  
Distribution of the number of images per room in the dataset SYMH.

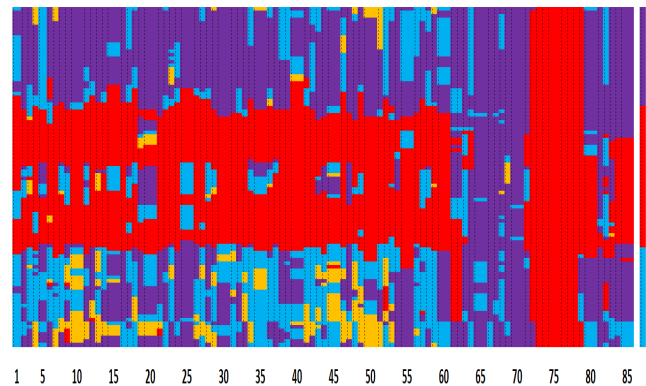
### 3. Experimentation

To evaluate our global framework, two databases were constituted: the first one called SYMH and the second one named Gladis.

**SYMH** has been collected from 4 healthy persons performing activities into a flat with different postures as defined section 2. The frame-rate per second (fps) of the depth devices is tuned to 2 fps. This dataset was manually annotated in order to perform supervised learning. Tables 3 and 4 display respectively the number of images registered per person and per room for each posture. In order to be as general as possible, we registered images from different views, with and without occlusions. The four healthy subjects participating to the study approved the trial and gave their consent and signed agreement to take part.

**Gladis** represents real-world situation where seniors (in retirement homes) are followed-up during months. The depth sensor were installed in a senior's bedroom in the Raymond Thomas retirement home in Rennes, France. This experimental trial was approved by the ethical review board of the nursing home and seniors participating gave their consent and signed agreement to take part. The images have been acquired every 15 min. This time was estimated enough to derive a global view of the day organization. The database contains 8160 depth images recorded over 85 days, which were manually annotated. The monitored person was a dependent person with mobility problems. The annotations for each sensor are distributed as follows: 1555 to the sitting position, 364 to falls, 3132 to the lying down position, and the remaining 3109 images correspond to the absence of the person. Fig. 5 represents the succession of the ground truth of the successive images during the day and for all the days (85 days) where the senior was monitored. Also, the routine day is presented next to the database. In this work and as proposed in section 2.3, the routine day is defined after

selecting the most frequent posture at a time  $t$  of recording for the 60 first days.



**Figure 5:** Annotations: sitting (blue), lying down (purple), absence (red) or falling (yellow), of the images during the day (y-axis) of the elderly person during 85 days (x-axis). The vertical line on the right represents his routine day.

We clearly see in Fig. 5 that the person has a routine during the first period (from the first day to 62nd day). By viewing the images recorded from the 62nd day, we can see that the person does not leave the room for 9 days and is often lying down on the bed. After the 9th day, the person is absent from the room and was hospitalized for 8 days. Then the senior came back. Indeed, we noticed that this senior falls once or twice a day, and that he leaves the room in the morning between 7:30 am and 8:30 am and comes back between 6:30 pm and 7:30 pm. At night, he sleeps between 10:30 pm and 01:30 am.

### 4. Results

The classification performance by the deep neural network are first introduced. Then in a second step, results related to the behavioral and the minimum edit distance indexes are presented. Finally, we analyze the evolution of these indexes during our experimentation.

#### 4.1. Image classification

As aforementioned, we used ResNet-18 for image classification. A data augmentation was applied such as random flipping and fake occlusion creation. As the content of a training database can have an impact on the classification result of a model, we tried different combinations of images coming either from the Gladis and SYMH databases or a mixture of both (Table 5). Pytorch on one GPU (Quadro RTX 3000) was used. The initial learning rate was set to  $1e-4$  and the Adam optimizer with a weight decay of  $5e-5$  was used for the optimization.

Table 6 shows the accuracy and F1-score using the different database combinations.

Good performances are obtained whatever the combination. However, as the methods for detecting behavioral changes are applied on the only elderly person in the Gladis database, we retained "Combination 1" to classify the recorded depth images.

Experimental	Learning base	Test base
Gladis only	80%	20%
SYMH only	80%	20%
Total bases	80% Gladis, 80% SYMH	20% Gladis, 20% SYMH
Combination 1	30% Gladis, 100% SYMH	70% Gladis
Combination 2	100% Gladis, 30% SYMH	70% SYMH

**Table 5**

Several combinations of data (Gladis and SYMH databases) for image classification.

Experimental	Accuracy	F1-score
Gladis only	92.02%	90.29%
SYMH only	98.50%	99.03%
Total bases	93.83%	94.03%
Combination 1	89.09%	85.84%
Combination 2	96.65%	96.69%

**Table 6**

Accuracy and F1-score results for different database combinations.

Fig. 6 displays the results of the prediction of the deep neural network for the test database. We observe an accuracy about 89.09% and a F1-score about 85.84%. Given that in the Gladis database, the senior never stood up, it is remarkable to see that the model is able to discriminate the class *standing* with others. It is also noticeable that most of the time, the model tended to classify *sitting* with *lying*. Such a confusion can be explained by the fact that the images are recorded from the ceiling. Indeed, from this point of view in height, a depth image of a seated person is close to a depth image of a person lying down. These figures also show that our model is able to discriminate the class *absent* from other classes. Such a result shows that the model should be able to analyze human shapes and infer from them.

true label \ predicted label	lying	sitting	fall	absent	stand_up
lying	1892	107	27	62	0
sitting	133	837	15	40	0
fall	7	29	165	8	0
absent	95	52	4	1835	0
stand_up	0	0	0	0	0

**Figure 6:** Confusion matrix on test database for posture recognition.

	Accuracy	Specificity	Sensitivity
<b>BRL</b>	74%	87%	52%
<b>DT</b>	88%	91%	84%
<b>RF</b>	92%	93%	90%

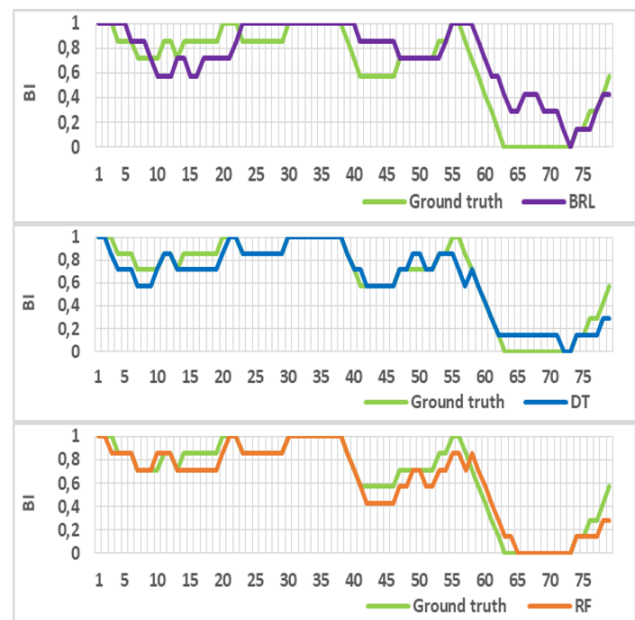
**Table 7**

Performance of the machine learning algorithms for daily routine classification. BRL stands for Binary Regression Logistic, DT Decision Tree and RF Random Forest.

## 4.2. Daily routine monitoring: behavior index

Binary Regression Logistic, Decision Tree and Random Forest were used to classify the day (routine/non routine with a Leave-one-day-out cross-validation method. Table 7 presents the performance of the three machine learning approaches.

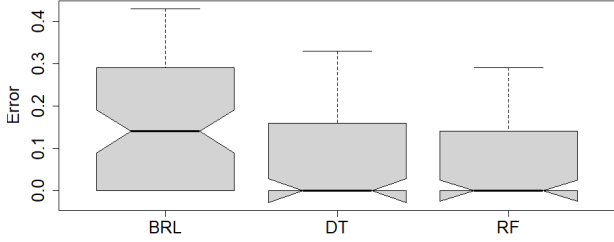
Fig. 7 shows the evolution of the  $BI_n$  Behavior Index during 85 days over a rolling P=7-day period when using *i*) the ground truth annotations (green line) and *ii*) the output of the classification using BRL, DT, RF.


**Figure 7:** Evolution of Index  $BI_n$  derived from ground truth annotation (green line) and from the classification of the postures.

We observe that the three  $BI_n$  functions derived from BRL, DT or RF have a trend comparable to the ground truth annotation  $BI_n$  function. It is worthwhile to mention that RF  $BI_n$  index confirmed the results reported in Table 7 and is closer to the ground truth  $BI_n$ .

Briefly, we observed from day one to day 63 that  $BI_n$  is quasi-constant ( $BI_n \in [0.6, 1]$ ) and translates that the routine is maintained. Then for the following 17 days, the senior no longer follows his daily routine and  $BI_n$  decreases. Then  $BI_n$  grows up and a progressive return to the routine is observed. This example shows that the proposed  $BI_n$  index highlights changes in the daily routine and could help in

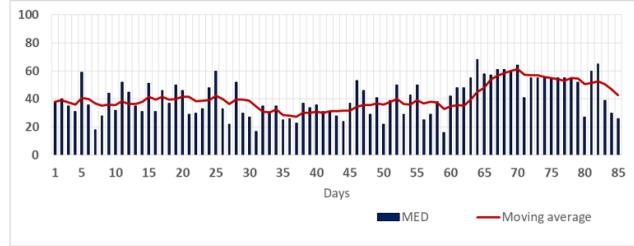
anticipating modifications in the health status of the senior. For each day, the absolute differences between the  $BI_n$  derived from the ground truth and from the classification approaches (BRL, DT, RF) were computed and depicted in Fig. 8. The results confirm clearly that RF produces a minimum median absolute error less than 0.01.



**Figure 8:** Boxplot of the absolute difference between the moving average of the real data and the moving average of the predicted data.

### 4.3. Daily routine monitoring: MED index

MED returns the number of changes to align the recorded day with the routine day. Fig. 9 shows the MED per day for the person, and the 7-day moving average of the number of MED.



**Figure 9:** MED between the routine day and the days recorded for the person. In red, the 7-day moving average of MED is depicted.

We notice in this figure that the MED shows an increase in the number of transformations from day 62 and a decrease from day 79.

To highlight the interest of the MED, the 85 days were empirically divided into 7 temporal windows (A, B, C, D, E, F, and G) of manually annotated homogeneous days. For example, group A, B, C, D correspond to day 1 to day 62 and are assumed as routine days. Group E and F, manually annotated as non-routine days, represent days 63 to 71 and days 72 to 78 respectively. While group G corresponds to days 79 to 85.

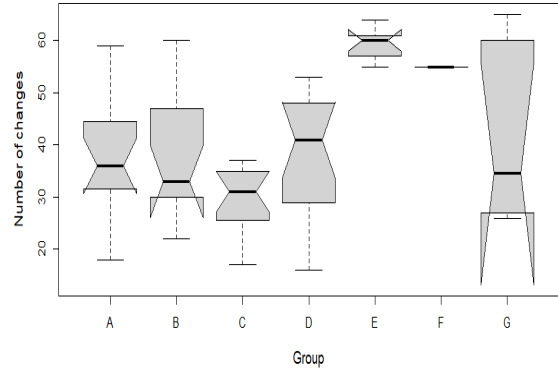
The MED per group is depicted as boxplots (Fig. 10) and the Wilcoxon test with multiple test groups is reported Table 8. The examination of Fig. 10 and Table 8 show that groups A, B, C, and D are not significantly different ( $p > 0.05$ ). Clearly we noticed that groups A, B, C and D have

	A	B	C	D	E	F
B	0.87					
C	0.061	0.176				
D	0.87	0.87	0.135			
E	0.001	0.002	0	0.001		
F	0.002	0.002	0	0	0.273	
G	0.952	1	0.362	0.87	0.187	0.421

**Table 8**

Result of the Wilcoxon test applied on the homogeneous 7 groups (A, B, C, D, E, F, and G) (see text for further details).

significant difference with groups E and F ( $p < 0.002$ ). It was also observed that the values of group G recover all the other groups. This is due to the fact that the senior comes back to his room after a hospitalization and progressively retrieves his routine.



**Figure 10:** Boxplot of the number of MED changes per group of days. See text for the definition of the groups A, B, C, D, E, F and G.

## 5. Discussion

Overall, this work proposes a general framework to detect the change in the person's behavior based on the monitoring of his daily routine. Routine in the elderly person is important for preserving autonomy and increasing sense of control over their day and environment [1, 22]. Routine also helps to reduce the risk of experiencing unexpected and unpleasant situations, and thus improves the feeling of well-being. In this article, we record elderly persons with depth sensors, that preserve his anonymity, to monitor their activities and to detect the behavior change. However, we must keep in mind that depth cameras can have some limitations such as a limited field of view, incomplete spatial data, noise, bad reflections on some material, bad acquisitions when strong sunlight is coming through a window, etc. The methods were applied on a database of a senior living in a nursing home over a long period (85 days). It is worthwhile to remind that such acquisition during such a long period is not an easy task.

From the recordings, we classify with deep neural networks the postures (sitting, lying, standing, absent and falling). An overall accuracy close to 89% was observed. Then we exploit these classification to characterize the routine with two behavioral indexes used for daily monitoring.

In the first index, the day is described by the percentages of sitting time, standing time, lying down time, absence time and the number of falls. According to these values, the day is classified as routine or non-routine. A comparative study between binary regression logistic, decision tree and random forest shown the superiority of the last approach with about 93% and 90% specificity and sensibility respectively. Then an automatic behavioral function  $BI_n$  is computed. A comparison between the ground truth annotations shows the interest of  $BI_n$  and a median absolute error less than 0.01 was measured.

In the second index, the day is described by a succession of postures. The MED computes the number of changes to switch from the recorded day to the routine day. When comparing the routine group (RG) by merging groups A, B, C, D-, and the non-routine group (NRG) -a fusion of groups E and F-, and by denoting med [Q25th, Q75th] the median and the interquartile range of the number of MED transformations, we reached for the RG 38[28, 48] and for the NRG 55[55, 62]. These results show quasi no-overlap between the two groups and confirm the reliability of the MED to perceive modifications in the daily routine of a senior.

During daily routine monitoring, our framework, to our knowledge, is one of the first observing on long period. Using several sensors such as Infra-red, door contact and kinect sensors or video, works have been conducted for activity recognition but do not address behavior change detection [26, 27]. In a smart home, [28] contributed to health status monitoring but the proposition remains as proof of concept on 1h and none performance on long time duration was reported. In [29], Forkan and al. propose very relevant and interesting solutions combining sensors in smart home, hidden Markov model and fuzzy logic. On 10 patients, they were able to detect abrupt abnormalities from the routine with an accuracy about 95%. Here, we thought to reduce the complexity by using one depth sensor and to focus on long duration persistent behavior changes. Interesting solutions were also proposed for fall detection [30, 4]. This is of course, one representative of behavior changes but do not characterize the overall routine. Our contribution appears as a continuation of these works going further by introducing behavior change indexes.

Lastly, two theoretical models of frailty are currently being accepted and used: Fried [31] and Rockwood [32]. In 2001, Fried proposed a model based on a physical phenotype that assesses the existence of five parameters (Unintentional weight loss, Feelings of exhaustion, Muscle weakness, Slow walking speed, Low levels of physical activity) in people aged 65 or over. In the presence of at least three factors

above, patients are frail. Rockwood in 2005 proposed another model of frailty integrating cognition, mood, motivation, motor skills, balance, abilities for activities of daily living, nutrition, social condition and comorbidities. Thus, the two methods of elderly follow-up (the degree of or change in the routine) proposed in this paper would be additional information to be combined with the frailty models described above. These models, applied at the time when the person is still robust, could be used to follow the routine and thus predict the frailty trajectory [3] which remains a complex multifactorial problem.

## 6. Conclusion

Methodologies and main results were summarized in the previous section. We preferred in this conclusion to draw some limitations of our study and offers prospects for improvements.

The main and the major drawback is of course the limited size of the database. It is envisaged to design a clinical study during several months and for several seniors in order to prevent or delay the first signs of disability and frailty.

For frailty detection, our feeling is that the approach developed in this work, which combines the classification of day (routine/non routine) and the minimal edit distance, is relevant. The first one offers a global view of the person's daily behavior over time without looking at the succession of activities. The second one proposes the chronology of the day's activities in time and space. Further studies will be dedicated in exploring this way for a better comprehension of the frailty.

## Acknowledgment

This work was part of the PRuDENCE project (ANR-16-CE19-0015) which has been supported by the French National Research Agency (ANR). The first author received also a scholarship from the Brittany Council. The authors would like to thank all the partners of the PRuDENCE project and also all the participants involved in the experimentation.

## References

- [1] V. Bergua, J. Bouisson, J.-F. Dartigues, J. Swendsen, C. Fabrigoule, K. Pérès, P. Barberger-Gateau, Restriction in instrumental activities of daily living in older persons: Association with preferences for routines and psychological vulnerability, *The International Journal of Aging and Human Development* 77 (4) (2013) 309–329. doi: 10.2190/AG.77.4.c.
- [2] S. Msaad, Y. Zoetgnande, J. Prud'homme, G. Cormier, G. Carrault, Frailty detection of older adults by monitoring their daily routine, in: 2020 IEEE 20th International Conference on Bioinformatics and Bioengineering (BIBE), IEEE, 2020, pp. 701–704. doi:10.1109/bibe50027.2020.00118.
- [3] P. N. Dawadi, D. J. Cook, M. Schmitter-Edgecombe, Modeling patterns of activities using activity curves, *Pervasive and Mobile Computing* 28 (2016) 51–68. doi:10.1016/j.pmcj.2015.09.007.
- [4] M. Saleh, R. Le Bouquin-Jeannes, Elderly fall detection using wearable sensors: A low cost highly accurate algorithm, *IEEE Sensors Journal* 19 (8) (2019) 3156–3164. doi:10.1109/JSEN.2019.2891128.



- [5] M. Abbas, D. Somme, R. Le Bouquin-Jeannès, Machine learning-based physical activity tracking with a view to frailty analysis, in: 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), 2020, pp. 3917–3920. doi: 10.1109/EMBC44109.2020.9175589.
- [6] Y. Li, Z. Zeng, M. Popescu, K. C. Ho, Acoustic fall detection using a circular microphone array, in: 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology, 2010, pp. 2242–2245. doi:10.1109/IEMBS.2010.5627368.
- [7] Y. Zigel, D. Litvak, I. Gannot, A method for automatic fall detection of elderly people using floor vibrations and sound – Proof of concept on human mimicking doll falls, *IEEE Transactions on Biomedical Engineering* 56 (12) (2009) 2858–2867. doi:10.1109/TBME.2009.2030171.
- [8] E. Auvinet, F. Multon, A. Saint-Arnaud, J. Rousseau, J. Meunier, Fall detection with multiple cameras: An occlusion-resistant method based on 3-D silhouette vertical distribution, *IEEE Transactions on Information Technology in Biomedicine* 15 (2) (2010) 290–300. doi: 10.1109/TITB.2010.2087385.
- [9] E. E. Stone, M. Skubic, Fall detection in homes of older adults using the Microsoft Kinect, *IEEE Journal of Biomedical and Health Informatics* 19 (1) (2015) 290–301. doi:10.1109/JBHI.2014.2312180.
- [10] L. Tao, T. Volonakis, B. Tan, Y. Jing, K. Chetty, M. Smith, Home activity monitoring using low resolution infrared sensor, *CoRR* abs:1811.05416 (2018). arXiv:1811.05416.
- [11] Y. Zoetgnandé, Fall detection and activity recognition using stereo low-resolution thermal imaging, Ph.D. thesis, Université de Rennes 1 (UR1) (2020).
- [12] A. Sixsmith, N. Johnson, R. Whatmore, Pyroelectric IR sensor arrays for fall detection in the older population, in: *Journal de Physique IV (Proceedings)*, Vol. 128, 2005, pp. 153–160. doi:10.1051/jp4:2005128024.
- [13] G. Cormier, Analyse statique et dynamique de cartes de profondeurs: application au suivi des personnes à risque sur leur lieu de vie, Ph.D. thesis, Université Rennes 1 (2015).
- [14] S. Msaad, G. Cormier, G. Carrault, Detecting falls and estimation of daily habits with depth images using machine learning algorithms, in: 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), 2020, pp. 2163–2166. doi: 10.1109/EMBC44109.2020.9175601.
- [15] A. Krizhevsky, I. Sutskever, G. E. Hinton, ImageNet classification with deep convolutional neural networks, *Advances in neural information processing systems* 25 (6) (2012) 1097–1105. doi:10.1145/3065386.
- [16] K. Simonyan, A. Zisserman, Very deep convolutional networks for large-scale image recognition, *CORR* abs:1409.1556 (2014). arXiv:1409.1556.
- [17] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, A. Rabinovich, Going deeper with convolutions, in: 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, 2015, pp. 1–9. doi:10.1109/CVPR.2015.7298594.
- [18] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, in: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 770–778. doi:10.1109/CVPR.2016.90.
- [19] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, L. Fei-Fei, ImageNet Large Scale Visual Recognition Challenge, *International Journal of Computer Vision (IJCV)* 115 (3) (2015) 211–252. doi:10.1007/s11263-015-0816-y.
- [20] A. L. Coleman, K. Stone, S. K. Ewing, M. Nevitt, S. Cummings, J. A. Cauley, K. E. Ensrud, E. L. Harris, M. C. Hochberg, C. M. Mangione, Higher risk of multiple falls among elderly women who lose visual acuity, *Ophthalmology* 111 (5) (2004) 857–862. doi: 10.1016/j.ophtha.2003.09.033.
- [21] R. G. Cumming, J. L. Kelsey, M. C. Nevitt, Methodologic issues in the study of frequent and recurrent health problems falls in the elderly, *Annals of epidemiology* 1 (1) (1990) 49–56. doi:10.1016/1047-2797(90)90018-n.
- [22] J. W. Reich, A. J. Zautra, Analyzing the trait of routinization in older adults, *The International Journal of Aging and Human Development* 32 (3) (1991) 161–180. doi:10.2190/4pkr-f87m-uxeq-r5j2.
- [23] W. Zhu, N. Zeng, N. Wang, et al., Sensitivity, specificity, accuracy, associated confidence interval and roc analysis with practical sas implementations, *NESUG proceedings: health care and life sciences*, Baltimore, Maryland 19 (2010) 67.
- [24] R. A. Wagner, M. J. Fischer, The string-to-string correction problem, *Journal of the ACM (JACM)* 21 (1) (1974) 168–173. doi:10.1145/321796.321811.
- [25] S.-R. Kim, K. Park, A dynamic edit distance table, *Journal of Discrete Algorithms* 2 (2) (2004) 303–312. doi:10.1016/s1570-8667(03)00082-0.
- [26] E. Kim, S. Helal, D. Cook, Human activity recognition and pattern discovery, *IEEE Pervasive Computing* 9 (1) (2009) 48–53. doi: 10.1109/MPRV.2010.7.
- [27] A. Fleury, M. Vacher, N. Noury, Svm-based multimodal classification of activities of daily living in health smart homes: sensors, algorithms, and first experimental results, *IEEE Transactions on Information Technology in Biomedicine* 14 (2) (2009) 274–283. doi:10.1109/TITB.2009.2037317.
- [28] N. K. Suryadevara, S. C. Mukhopadhyay, R. Wang, R. Rayudu, Forecasting the behavior of an elderly using wireless sensors data in a smart home, *Engineering Applications of Artificial Intelligence* 26 (10) (2013) 2641–2652. doi:10.1016/j.engappai.2013.08.004.
- [29] A. R. M. Forkan, I. Khalil, Z. Tari, S. Foufou, A. Bouras, A context-aware approach for long-term behavioural change detection and abnormality prediction in ambient assisted living, *Pattern Recognition* 48 (3) (2015) 628–641. doi:10.1016/j.patcog.2014.07.007.
- [30] N. Noury, A. Fleury, P. Rumeau, A. K. Bourke, G. Laighin, V. Rialle, J. Lundy, Fall detection-principles and methods, in: 2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2007, pp. 1663–1666. doi:10.1109/iembs.2007.4352627.
- [31] L. P. Fried, C. M. Tangen, J. Walston, A. B. Newman, C. Hirsch, J. Gottdiener, T. Seeman, R. Tracy, W. J. Kop, G. Burke, et al., Frailty in older adults: evidence for a phenotype, *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences* 56 (3) (2001) M146–M157. doi:10.1093/gerona/56.3.m146.
- [32] K. Rockwood, X. Song, C. MacKnight, H. Bergman, D. B. Hogan, I. McDowell, A. Mitnitski, A global clinical measure of fitness and frailty in elderly people, *Cmaj* 173 (5) (2005) 489–495. doi:10.1503/cmaj.050051.