Assessing the Frailty of Older People using Bluetooth Beacons Data

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***Abstract*— Sensor-based quantitative assessment of frailty in older adults usually requires expensive wearables or ambient sensors. However, low cost activity tracking systems can be effective in discriminating frailty characteristics. In this work, a system for assessment of the frailty of older people is presented, based on the analysis of data describing the daily in-house activity. More specifically, room-to-room movements are recorded using a set of Bluetooth beacons, located in fixed positions inside each room. A smartphone is used to locate the timestamps of room transitions, and these are used to calculate the time spent in each room, thus generating the time intervals signal. Then, several features depicting the in-house mobility are extracted from each signal and are evaluated, in terms of correlation with the subject's frailty status. Furthermore, the features are used to train a classifier for frailty assessment. Two approaches are evaluated, with different number of levels of frailty, and the results indicate that this procedure can lead to reliable older people frailty assessments, especially when two levels of frailty are considered.**

Keywords—frailty level assessment, elder people, Bluetooth beacons

I. Introduction

Frailty is a condition of increased vulnerability and decreased endurance appearing in ageing population, caused by a cumulative decline in the physiologic systems of an individual, resulting in increased risk of disability, morbidity, psychological decline, hospitalization or death. The increased vulnerability of frail older persons to stressors and health implications also has an impact in the effective healthcare planning and delivery by healthcare organizations. Early detection of frailty indicators in the individual's health status can assist in preventing or delaying frailty symptoms, or even reversing the process [1].

Assessment of frailty is often based on quantitative phenotypical criteria, such as unintentional weight loss, exhaustion, weakness, slow walking speed and low physical activity, as used in the widely-used Fried frailty index [2]. These criteria are mostly gathered through questionnaires or interviews with the individuals. Such measurements are commonly collected during clinical sessions or visits of clinical personnel to the older person's premises, thus they are usually considered as impractical for continuous care. Unobtrusive measurement of health status using real-time monitoring through sensors (wearable or ambient) can significantly assist in the collection of more comprehensive data and the early detection of adverse outcomes. Wearables have been used for monitoring key phenotypical characteristics related to frailty, such as weakness, slowness and exhaustion [3]. Activity monitoring can prove valuable for assessing frailty, since it is directly relevant to frailty indicators, while at the same time it can be performed constantly, in a manner that is unobtrusive for the older person.

In this paper, a study is performed to assess the correlation between simple measured indoor activities of an older person and his/her frailty status, as assessed by well-known frailty criteria. The measurements of activity are collected by monitoring the position of the older person in the house, at room level. Monitoring is performed by an application focused on ease of installation and usage by the individual, through the use of Bluetooth beacons placed within the area. Several features of activity are extracted from the raw measurements, related to room transitions and to how long the person spends in a room, and are assessed in terms of their correlation to the frailty status. The features are then used to train frailty status predictors, and to evaluate the accuracy of predicting the person's frailty status using the measured activity data.

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II. RELATED WORK

Traditionally, frailty has been assessed using well-known and commonly used metrics, such as the Fried index [2], which uses phenotypical characteristics (shrinking, weakness, poor endurance, slowness and low physical activity) to determine the frailty level of an individual (non-frail, pre-frail, frail). Similar metrics have also been based on several types of clinical indicators, such as cognition, mobility, function, social health, medications, co-morbidities, etc., or using different severity levels [4-6]. Activity-related indicators, such as the IADL (Instrumental Activities of Daily Living) grade have also been used, as they provide significant frailty-related information [7]. Although these metrics are well-established, they are based on data collected during infrequent clinical evaluations requiring the supervision of clinical personnel.

Instead of relying on one-time clinical evaluations, continuous monitoring through sensors has been used as a way to achieve constant and automatic monitoring. An upper body wearable system proposed in [8] was able to objectively assess the frailty status. The system presented in [9] is an example of a system for continuous monitoring of activity-related information, such as gait speed and activity recognition, targeted at the detection of frailty risk.

Recently, the authors of [10] have used a motion identification system using accelerometers and gyroscopes, in order to be used for frailty assessment. Daily activity patterns have been extracted from ambient sensors and used for unobtrusive detection of unusual behaviours [11-12] and rehabilitation [13]. Combinations of multiple types of sensors have also recently been used in more holistic assessments of frailty [14]. Studies have been performed to assess the discriminating capability of activity-related data to frailty-related indicators, leading to promising results [15-17].

Regarding the extraction of mobility patterns, motion sensors have frequently been used to monitor the individual's movements [11-12]. However, localization-based methods are a lower cost alternative for activity detection. Comparative studies of Bluetooth, WLAN, RFID, UWB (Ultra-Wide Band) and ultrasound systems have shown their applicability for meter-level localization [18].

Methods utilized for localization include trilateration and triangulation, where distances of a tracked device from known points are used to compute the tracked device position [19], as well as fingerprinting, where signal fingerprints are collected beforehand from several positions and used to estimate the current position [20-21]. However, such techniques usually require significant training, which may be prohibitive for medical applications in home environments.

III. EXPERIMENTAL SETTING & DATASET

A. Bluetooth Beacons

The beacons are small passive devices using Bluetooth Low Energy (Fig. 1). Most of the existing beacons in the market use batteries as energy source, which last for months or even a couple of years. Their function is to broadcast, between small time intervals, messages in the 2.4GHz band which contain information about their ID. These messages are used from the tracking device, in our case a smartphone, in order to estimate the position of the monitored person with room level accuracy. The tracking device process continuously the RSSI (Received Signal Strength Indicator) values from the beacons to make this estimation. RSSI values, measured in dBm are associated with the distance between beacon and the tracking device. In general, the smaller the distance of the tracking device from the beacon the greater the measured RSSI values are.

Fig. 1. The Sensoro Bluetooth beacons used in our Bluetooth localization system. They were chosen mainly due to their long lasting batteries their low cost and their quality.

B. Experimental Process

The application is developed with the aim of being easy to install by the clinical personnel and easy to be used by the older persons. The Bluetooth-based application, developed for indoor localization monitoring, consists of two stages. One for training, to be used from the medical personnel, and one to be used from the monitored person. The training procedure includes a 30 second walk in the area of each room of the monitored house, in order to collect RSSI measurements, known as fingerprints. Each room is associated with a specific RSSI fingerprint. During the indoor localization phase the tracking device continuously collects RSSI measurements from the beacons and compares them with the stored fingerprints. The monitored person's position is in the room with the most similar fingerprint. To measure the similarity the Euclidean distance is used. The number of beacons used in the most houses was five, placed in fixed positions with distances greater than 2m between them. An example of a beacon placement in a house can be seen in Fig. 2.

Fig. 2. An example of a beacon placement. The coloured areas represent the areas for each room where the medical personnel walks for 30 seconds in order to collect the RSSI fingerprints.

C. Subjects

This study included data from 73 subjects, 25 males and 48 females, Data recording included the frailsafe_id, the frailty status and the subject's location, birth year, gender, profession and education years. The frailty status is defined as non-frail, pre-frail and frail. The number of subjects in each frailty status is presented in Table I.

TABLE I. FRAILTY STATUS OF SUBJECTS

Frailty Status	Total subjects (males/females)
Non-frail	26 (6/20)
Pre-frail	27 (11/16)
Frail	20 (8/12)

Subjects were recruited in three different locations, being Patras (Greece), Nicosia (Cyprus) and Nancy (France). The birth year was used to define the age of each subject: the dataset included subjects with ages of 77.5±5.3 years old for males and 78.8±5.7 years old for females.

D. Collected Data

The collected dataset contains records produced by the indoor localization system used in the FrailSafe project, which is based on Bluetooth beacons. The indoor localization system was installed in the house of each subject for a number of days, varying from 1 to 7. In Fig. 3, a histogram depicting the number of patients having a specific number of recording days, is presented.

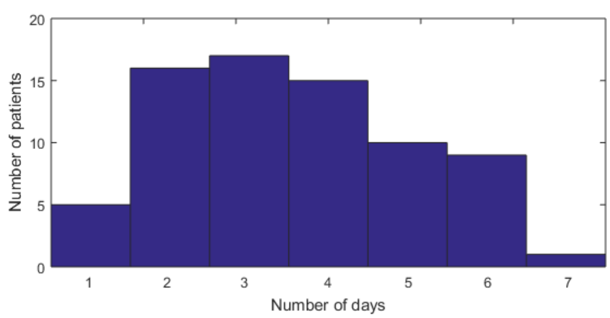

Fig. 3. Record generated from the experimental setting of the Bluetooth.

The indoor localization system works as follows: firstly the medical personnel place the beacons in fixed positions and create the RSSI fingerprints of each room with a 30 second walk as described in the previous section. Then, the subject that will be monitored moves around the house, performing regular activities of daily living, and he/she is instructed to carry a mobile phone at all time. The mobile phone continuously measures the RSSI values from the beacons of the house. When the subject enters a room, the RSSI measurements gradually change and become similar with the RSSI fingerprint of the specific room then a transition is created including the label of the room and the timestamp. Thus, while moving around the house, a record of room transitions is generated.

An example of the room transitions record (generated a CSV file) is illustrated in Fig. 4, with each row corresponding to a room transition. The room labels have been registered by the clinical personnel, during the installation process of the hardware.

```
deviceID,userID,username,room,timestamp
9154a9a6beee766d,1003,,Livingroom,20170928160607
9154a9a6beee766d,1003,,Bathroom,20170928160638
9154a9a6beee766d,1003,,Livingroom,20170928160645
9154a9a6beee766d,1003,,Hall,20170928160657
9154a9a6beee766d,1003,,Kitchen,20170928160719
9154a9a6beee766d,1003,,Hall,20170928160736
9154a9a6beee766d,1003,,Livingroom,20170928160742
9154a9a6beee766d,1003,,Hall,20170928160900
9154a9a6beee766d,1003,,Livingroom,20170928161012
```

Fig. 4. Room transitions record.

Each record contains the following fields:

- deviceID: a unique ID for the mobile phone carried by the person,
- userID: the FrailSafe user ID of the older person,
- username: the username of the subject, in the FrailSafe system,
- room: the room that the older person just got into,
- timestamp: the timestamp at the time that the user moved inside the room, in "YYYYMMDDhhmmss" format.

All available data from all patients were included in the analysis.

IV. DATA ANALYSIS & RESULTS

A. Signal Extraction

The records include the timestamps of transitions among the rooms. In order to proceed with the analysis, the time interval of the actual subject's presence in each room is initially calculated. Thus, the interval between each two successive transitions in each record is calculated. Thus, a sequence of time intervals was generated, with each representing the time that the subject remained in the same room. Each time interval is annotated with the characterization of the room that the subject was inside during this interval (i.e. the room of the first of the two successive transitions). An example of the time interval and the room annotations (generated using the input from Fig. 4) is illustrated in Fig. 5. An example of the time intervals signal is presented in Fig. 6.

```
timeinterval,room
31,Livingroom
7,Bathroom
12,Livingroom
22,Hall
17,Kitchen
6,Hall
78,Livingroom
72,Hall
```

Fig. 5. Time interval and room annotations.

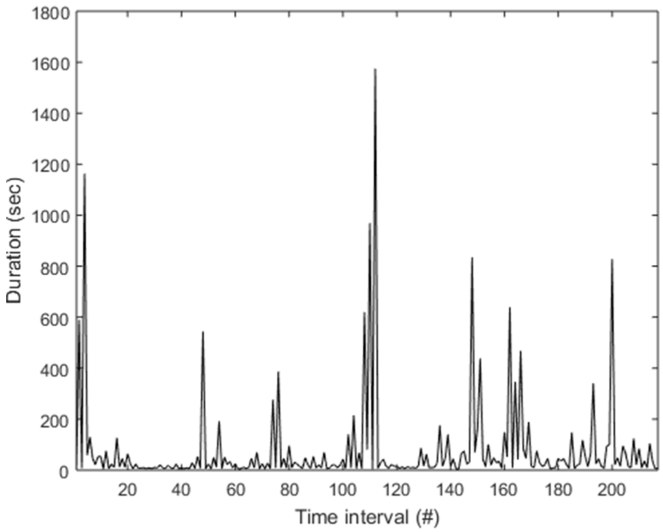

Fig. 6. Time intervals signal. This signal coresponds to a room transitions record of 4 hours and 43 minutes.

B. *Singal Preproseccing*

The initial records included several issues that should be addressed before the analysis could be performed.

a) Beacon hopping phenomena

During the recordings, several "beacon hopping" phenomena occurred, i.e. the room transitions record included several lines indicating that the subject was continuedly moving between to rooms with <=2 sec between transitions. This mainly indicates that the subject was located in a position covered from two beacons at the same time and doesn't correspond to actual subject's room movements. All these type transitions are detected and eliminated from the time interval signals, using the following procedure:

1. Detect a sequence of at least three consecutive time intervals with duration <= 2 sec records.
2. Merge all time intervals in the sequence into a single time interval.
3. Use the room annotation of the initial time interval in the sequence, as annotation of the merged time interval.

b) Non-activity periods

Prolonged presence in the same room (more than 3600 sec) is considered as non-activity periods and are excluded from the study, by using the data before and after this period. Thus, if a time interval signal contained one non-activity period, the signal is split in two parts, the first from the start of the signal until the time interval before the non-activity period, and the second from the time interval after the non-activity period, to the end of the signal. Then, the process resumes the search for non-activity periods from the second part of the signal.

c) Signal Segmentation

The analysis focused on 1800 sec time periods, thus each signal generated after "beacon hopping" correction and non-activity periods removal, is segmented into several non-overlapping time interval signals, with at least 1800 sec duration. Since these time periods are defined based on the running sum of the time intervals in each signal, the actual duration of each signal varies according to the duration of the last time interval. A total of 254 signals are generated after signal segmentation. In Fig. 7, a graphical illustration of the duration of the time interval signals versus the room transitions included in each time interval signal, is presented.

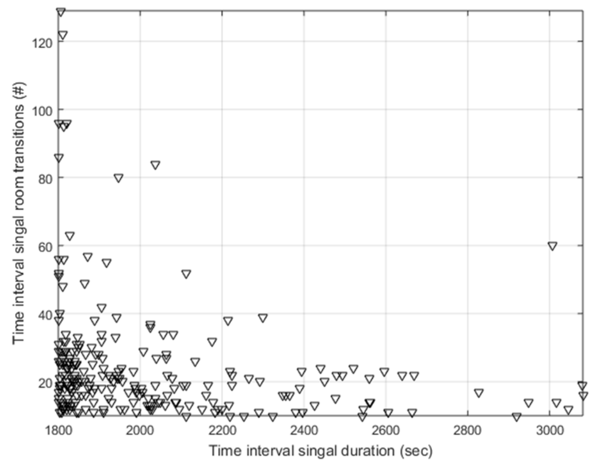

Fig. 7. Signal duration (sec) versus number of room transitions, in each time interval signal.

The average duration of the time interval signals is 2024(±281.8) sec while the average number of room transitions is 24.5(±17.6) transitions. Histograms of the time interval signal duration (sec) and number of room transitions, are presented in Fig. 8.

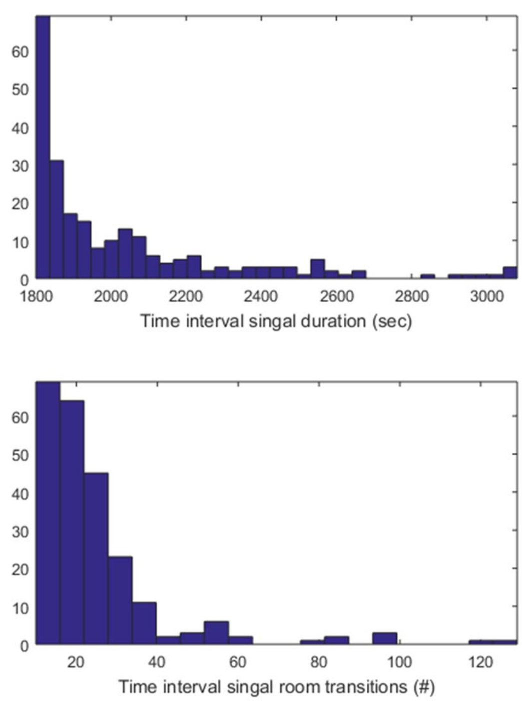

Fig. 8. Histogram of the duration of the time interval signals (above) and the number of room transitions (below).

C. Feature Extraction

The time interval signals generated after the signal preprocessing stage, are used for feature extraction. The features extracted from each signal are presented in Table II.

TABLE II. FEATURES EXTRACTED FROM EACH TIME INTERVAL SIGNAL

Feature	Description
Number of room transitions	The number of total room transitions in the time interval signal
Room transition average time duration	The average of the time intervals in the time interval signal
Room transition standard deviation of time duration	The standard deviation of the time intervals in the time interval signal
Number of fast room transitions	Number of time inervals with duration <= 15 sec
Number of slow room transitions	Number of time inervals with duration > 600 sec
Percentage of fast room transitions	Ratio of the number of fast room transitions to the number of room transitions.
Percentage of slow room transitions	Ratio of the number of slow room transitions to the number of room transitions.
Normalised number of fast room transitions	$\frac{\text{Number of slow room transitions}}{\left(\text{Number of rooms}\right) * \left(\text{Number of room transitions}\right)}$
Normalised number of slow room transitions	$\frac{\text{Number of fast room transitions}}{\left(\text{Number of rooms}\right) * \left(\text{Number of room transitions}\right)}$

The number of rooms used in the normalised number of fast/slow room transitions is the number of rooms covered by beacons, since this is not always the same for all subjects. Also, the frailty status of the subject that the time interval signal corresponds, is also included in the features.

D. Statistical Analysis

Initial, statistical analysis is performed to the obtained features, in order to evaluate the correlation of each feature with the frailty status. Since frailty is not a continuous variable, a non-parametric test is used, thus the two-tailed Spearman's rank correlation is employed. The obtained results are presented in Table III.

E. Frailty Level Assesment

In order to create a model for frailty level assessment, the calculated features are used for a classification process. The classification dataset includes 254 samples (98 annotated as non-frail, 94 as pre-frail and 62 as frail) and 10 features (including annotation), while classification is performed for all three classes. Several well-known classification schemes have been employed in the process, being Naïve Bayes classifier (NB), k-Nearest Neighbour with k=5 (kNN), Neural Networks (NN), Decision Trees with theC4.5 algorithm (DT), and Random Forests (RF). The 10-fold stratified cross-validation is employed in all classification cases.

TABLE III. SPEARMAN'S CORRELATION COEFFICIENT RESULTS

Feature	Coefficient
Number of room transitions	0.94
Room transition average time duration	-0.14
Room transition stdev of time duration	0.088*
Number of fast room transitions	0.507**
Number of slow room transitions	0.052
Percentage of fast room transitions	0.57**
Percentage of slow room transitions	0.01
Normalised number of fast room transitions	0.568**
Normalised number of slow room transitions	0.03

* significant at the 0.05 level
** significant at the 0.01 level

Results are obtained in terms of average sensitivity, defined as the average of the sensitivity obtained for each class, average positive predictive value (PPV), defined as the average of the positive predictive value obtained for each class, and classification accuracy. The results are presented in Table IV.

TABLE IV. RESULTS FOR THE 3-CLASS PROBLEM

Classifier	Average Sensitivity	Average PPV	Classification Accuracy
NB	46.37%	45.73%	48.43%
kNN	47.19%	46.67%	49.21%
NN	51.96%	51.21%	50.79%
DT	53.62%	54.44%	55.51%
RF	54.15%	54.58%	55.51%

Furthermore, Principal Components Analysis (PCA) is performed, in order to reduce the number of features. After PCA the number of retained attributes is set so as they cover 95% of the total variance, resulting to 5 new attributes. The obtained results using PCA are presented in Table V.

TABLE V. RESULTS FOR THE 3-CLASS PROBLEM USING PCA

Classifier	Average Sensitivity	Average PPV	Classification Accuracy
NB	44.58%	45.24%	47.64%
kNN	47.77%	47.51%	48.82%
NN	50.67%	50.45%	50.00%
DT	53.66%	53.84%	54.69%
RF	58.30%	59.09%	59.06%

The confusion matrix of the RF classifier applied to the data after using PCA (which achieved the highest results) is presented in Table VI.

TABLE VI. COMFUSION MATRIX FOR THE RF CLASSIFIER

		Classified		
		Non-frail	**Pre-frail**	**Frail**
Dataset	**Non-frail**	64	27	7
	Pre-frail	19	53	22
	Frail	4	25	33

Since from the results presented in Table VI, it is clear that the major misclassifications occur in the “pre-frail” class, which is the class describing the status of people between “non-frail” and “frail” classes, a two-class problem, focusing only on those two classes, is also performed. In this case, samples annotated as “pre-frail” are excluded, resulting to a dataset that includes 160 samples (98 “non-frail”, 62 “frail”) and the same number of samples. Again, results are obtained without and with the employment of the PCA, presented in Tables VII and VIII.

TABLE VII. RESULTS FOR THE 2-CLASS PROBLEM

Classifier	Average Sensitivity	Average PPV	Classification Accuracy
NB	74.09%	75.14%	76.25%
kNN	73.67%	73.67%	75.00%
NN	82.70%	81.09%	80.63%
DT	79.61%	78.47%	79.38%
RF	79.10%	77.90%	78.75%

TABLE VIII. RESULTS FOR THE 2-CLASS PROBLEM USING PCA

Classifier	Average Sensitivity	Average PPV	Classification Accuracy
NB	69.47%	72.27%	73.13%
kNN	75.49%	75.65%	76.88%
NN	77.53%	78.50%	79.38%
DT	83.94%	82.24%	82.50%
RF	76.30%	76.30%	77.50%

Classification accuracy results obtained for all classifiers, without and with PCA, for both 2 class and 3 class problems, are graphically illustrated in Fig. 9.

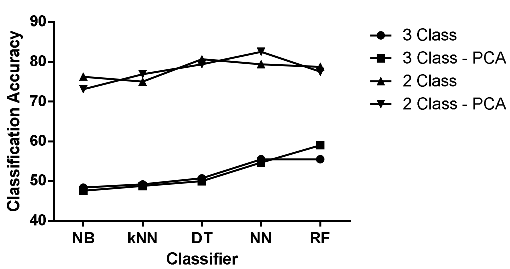

Fig. 9. Classification accuracy results.

V. DISCUSSION

In this study, a system using Bluetooth beacons and analysing data obtained from them in order to assess the frailty status of older people, is presented. The system is unobtrusive, easy to use and low-cost, since it includes Bluetooth beacons and smartphones. Also, it is easily expandable to more subjects in the same house, just by having each subject using a different smartphone device. Furthermore, the application of the proposed system has no security hazards, since the beacons broadcast only their ID; no location data or personal information of the subjects are broadcasted.

After preprocessing, the data are segmented into several time duration signals and several features are extracted from these signals. Statistical analysis in terms of correlation of each feature with the frailty status, and classification of the frailty status are performed. The statistical analysis of the extracted features revealed several features that present statistically significant correlation with the frailty status: “number of fast room transitions”, “percentage of fast room transitions” and “normalised number of fast room transitions” present correlation coefficient that is significant at 0.01 level, however the latter two are related with the first one (i.e the “number of fast room transitions”), since it is used for their calculation. Furthermore, the “room transition stdev of time duration” feature presents correlation coefficient that is significant at 0.05 level. However, “number of slow room transitions” and related features (“percentage of slow room transitions” and “normalised number of slow room transitions”) did not present statistically significant correlation with frailty status.

The classification accuracy results for the 3-class problem are not high, varying from 47.64% to 59.06%. However, this can be partially explained based on the confusion matrix (Table VI). The misclassification cases from/to pre-frail class are very high, since:

- 27 non-frail cases misclassified as pre-frail (79.4% of all non-frail misclassified cases and 26% of the overall misclassified cases),
- 19 pre-frail cases misclassified as non-frail (46.3% of all pre-frail misclassified cases and 18.3% of the overall misclassified cases),
- 25 frail cases misclassified as pre-frail (86.2% of all frail misclassified cases and 24% of the overall misclassified cases),
- 22 pre-frail cases misclassified as frail (53.7% of all non-frail misclassified cases and 21.2% of the overall misclassified cases).

Thus, the misclassified cases of non-frail/frail classes from/to pre-frail class correspond to the 89.4% of the overall misclassified cases, with the respective misclassification rate between the non-frail and frail classes being 10.6%. Thus, it is clear that the pre-frail class presents significant similarities with the non-frail and frail classes and is not distinctively defined based on the set of features used in this study. The obtained results for the 2-class problem further support this claim, ranging from 75% to 82.5%, demonstrating that the frailty level of a subject can be reliably assessed when non-frail and frail levels are considered.

VI. Conclusions

A novel approach for frailty status assessment of elder people based on features depicting their in-house room-to-room movement is presented in this study. Contrary to existing work, the proposed method is based on a low-cost localization-based system for activity pattern extraction, which focuses on easy installation and limited training by clinical personnel in home environments. The obtained results indicate that the frailty status can be assessed using beacon sequential data, yet the 3-class problem presents average results (with maximum accuracy being 59.06%) while for the 2-class problem, the results are high, achieving 82.50% classification accuracy.

Future work will focus on calculating and using additional features, that can more accurately assess the frailty status. Furthermore, the data are sequential, thus sequence analysis algorithms (such as sequential pattern mining) can also be applied. Also, the authors will focus on evaluating the data-analysis methodology with additional data from new subjects.

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