12-2020

Prediction of nocturia in live alone elderly using unobtrusive in-home sensors

Barry NUQOBA

Hwee-Pink TAN

Published in 2020 IEEE International Conference on Big Data (Big Data), pp. 4929-4937. DOI: 10.1109/BigData50022.2020.9377949.

Prediction of Nocturia in Live Alone Elderly Using Unobtrusive In-Home Sensors

Barry Nuqoba
School of Information Systems
Singapore Management University
Singapore, Singapore
barrynuqoba.2019@phdcs.smu.edu.sg

Hwee-Pink TAN
School of Information Systems
Singapore Management University
Singapore, Singapore
hptan@smu.edu.sg

***Abstract*—Nocturia, or the need to void (or urinate) one or more times in the middle of night time sleeping, represents a significant economic burden for individuals and healthcare systems. Although it can be diagnosed in the hospital, most people tend to regard nocturia as a usual event, resulting in underreported diagnosis and treatment. Data from self-reporting via a voiding diary may be irregular and subjective especially among the elderly due to memory problems. This study aims to detect the presence of nocturia through passive in-home monitoring to inform intervention (e.g., seeking diagnosis and treatment) to improve the physical and mental health of community-dwelling elderly living alone. With continuous and objective data from motion sensors installed in each zone of the apartment (bedroom, living room, kitchen, and bathroom) and a contact sensor on the main door from 39 elderly, we derive a sensor-based nocturia classification model, where nocturia labeling is done based on psychosocial survey data. Our evaluation of the model reveals that (i) the use of sensor-derived features (e.g., bedroom and living room occupancy and activity level as well as going out patterns) beyond nocturia events and (ii) the extraction and use of usual sleep location as a feature improves the classification performance, where perfect accuracy can be achieved with support vector machine. Further analysis on the survey findings also reveals that elderly with nocturia are more likely to have poor sleep quality, and suffer from conditions related to physical frailty. Our findings lend support to the efficacy of passive in-home monitoring as a digital biomarker for detection of nocturia and related conditions in live-alone elderly.**

***Index Terms*—nocturia, sensors, IoT, elderly, unobtrusive**

I. Introduction

Lower urinary track symptoms (LUTS) are estimated to affect 2.3 billion individuals, or 45.8 % of the world population in 2018, an increase of 18.4 % since 2008. Previous studies [2], [12], [23] have shown that nocturia, among others, has become one of the most distressed LUTS. The International Continence Society (ICS) defines n octuria a s t he n eed t o u rinate o ne or more times in the middle of night sleeping [1], [30].

Nocturia has major negative impacts on quality of life (QoL), both physically and mentally [11], [14], [16], [17], [21]. A survey study [17] revealed that nocturia is highly correlated with depression. Sleep disturbance caused by nocturia is the primary cause of the decline in QoL as the resultant tiredness and fatigue disturbs daytime behaviour [11], [26]. Although nocturia can be present in both genders and across all ages, its prevalence is higher in older adults [11], [18], [25]. The impact of nocturia on sleep quality is more significant among elderly aged 65 years and older [31], where going to the bathroom not in a fully awake condition in the middle of night sleeping is one of the primary causes of fall events and fractures [3], [11]. In fact, the medication cost for hip fractures caused by nocturia alone was around €1.0 billion in the EU in 2014 [11]. Besides the medical costs, reduced productivity at the workplace due to nocturia resulted in an economic impact of approximately €29.0 billion [11]. In the United States, medical costs due to falls caused by nocturia were around $1.5 billion each year, and the additional costs due to reduced productivity were approximately $61 billion [11].

Conventional assessment of nocturia can be done in the hospital using several methods, for example, through questionnaires such as the International Prostate Symptom Score (IPSS) [6], the Bristol Female Lower Urinary Tract Symptoms (BFLUTS) [4], and the International Consultation on Incontinence Questionnaire Male Lower Urinary Tract Symptoms Module (ICIQ-MLUTS) [7]. However, as most people tend to regard nocturia events as usual, and not correlated with any physical or mental condition, they tend not to seek treatment, resulting in underreported diagnosis and treatment [5], [22]. While self-reporting via a voiding diary can be useful for assessing nocturia, this could be limited due to subjectivity of reporting [32] as well as memory problems, especially among the elderly [29]. Furthermore, chronic cognitive impairments can bias the above assessment methods as they are highly dependent on patient reports [24].

However, the increasing pervasiveness of sensor, communication and computing technologies, as well as data science, enables the (i) continuous and passive in-home monitoring of day-to-day activities of the elderly; (ii) sense-making of objective data for intelligent detection and notification of anomalous events for timely intervention. SHINESeniors [19] investigated the actual use of sensor-enabled homes to enable 100 senior Singaporeans who live alone to age-in-place in the community. Analysis of the sensor data, alongside psychosocial survey data as well as ad-hoc observations made during home visits by the research team, enables a holistic study to address the (i) immediate and personal safety needs of the elderly (reactive care) and (ii) long-term health and social needs of the elderly (preventive care).

In alignment with the preventive care work stream of SHINESeniors, this study aims to detect the presence of nocturia through objective and continuous in-home sensor data and psychosocial survey data to inform intervention to improve the physical and mental health of the elderly. We describe related work on the use of objective data for nocturia detection in Section II. In Section III, we describe the data sources and our approach to data preparation and feature extraction. The results of sensor-based nocturia classification using ground truth labeling based on survey data collected are presented in Section IV. In addition, by studying the relationship between nocturia and other conditions as extracted from the survey, we explore the use of sensor-derived features for detecting nocturia as digital biomarkers for other conditions in Section V, as it has been shown in [28] that nocturia is a useful digital biomarker for cardiovascular diseases. Finally, we conclude the paper and outline possible future research directions in Section VI.

II. Related Work

To date, several researchers have conducted research on the use of objective and continuous data to overcome the limitations of existing methods of detecting nocturia. In [13], the authors measured toileting activity using a wristwatch and achieved good accuracy. However, the need to wear the wristwatch can give rise to inconvenience to the users. Moreover, the devices are also prone to damage as they are worn while the users are engaged in various daily activities. In another research [27], the authors examined the odor from urine using a device called Electronic Nose. While this study is related to toileting activities, it is focused on identifying the presence of diabetes on patients. The authors in [10] also studied toileting activities, specifically by proposing a method for measuring the amount of urine in the bladder. Although the authors in [29] developed a device that can detect elderly toileting activity, the need to replace one of the system components every 20 days to avoid measurement bias limits its use at large scale.

In SHINESeniors, the use of passive sensing mitigates the need for active participation by the elderly while permitting continuous, objective and unobtrusive in-home monitoring of the elderly at home. In addition, the battery-powered sensor devices have been shown to last for 300 days on average, enabling at-scale deployment to 100 elderly. Prior research on sensor-enabled preventive care for SHINESeniors has also achieved promising results for detecting elderly at risk of poor sleep quality [20], social isolation [9] and frailty deterioration [8].

III. In-Home Sensor-Based Nocturia Detection

In this section, we describe our approach towards in-home sensor-based nocturia detection as illustrated in Fig. 1. Specifically, we first describe the data sources used in this study in Section III-A. Following this, our approach towards data preparation and feature extraction is described in Section III-B and III-C respectively.

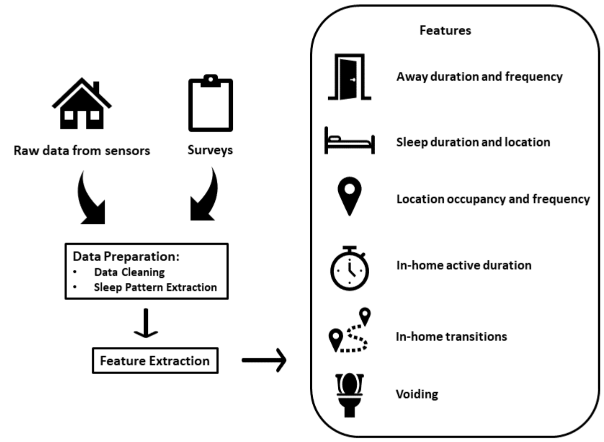

Fig. 1. Framework for In-Home Sensor-Based Nocturia Detection.

A. Data Sources

The data used in this study are obtained from elderly who consented to participate in the SHINESeniors project. All participants are aged 65 years and older, live alone in government-subsidized apartments, and are affiliated to a caregiver organization in the local community. The project installed passive infrared (PIR) motion sensors in each zone of the elderly's home as well as a door contact sensor on the main door (See Fig. 2). Each row in the sensors data consists of information such as device id, device location, the time when the sensor fires, and the value generated by the sensor (See Fig. 3). Each motion sensor fires a signal of movement (value = 255) if it detects motion after a minimum of four minutes of non-motion; otherwise, it fires a message of non-motion (value = 0) if no movement is detected within four minutes after the last movement. The door contact sensor fires a signal each time the door is opened (value = 255) or closed (value = 0).

Apart from collection of continuous and objective sensor data, which began in early 2015, psychosocial surveys focusing on basic demographics, toileting habits, sleeping habits, depression, and physical health status of each elderly were conducted every 6 months. The ground truth for nocturia classification is obtained from responses to questions about toileting habits, i.e., questionnaires using BFLUTS [4] and ICIQ-MLUTS [7] for female and male elderly, respectively. Specifically, based on the answer to the question: "How many times during the night you have to get up to urinate, on average?", the elderly is classified as normal if the answer is 0 and nocturia otherwise [1].

For this study, we considered the results of two psychosocial surveys conducted in around March 2018 and December 2018 to serve as the ground truth. Accordingly, sensor data up to one month prior to the survey date of each elderly (See Fig. 4) is used for the subsequent steps. The reason is that nocturia is

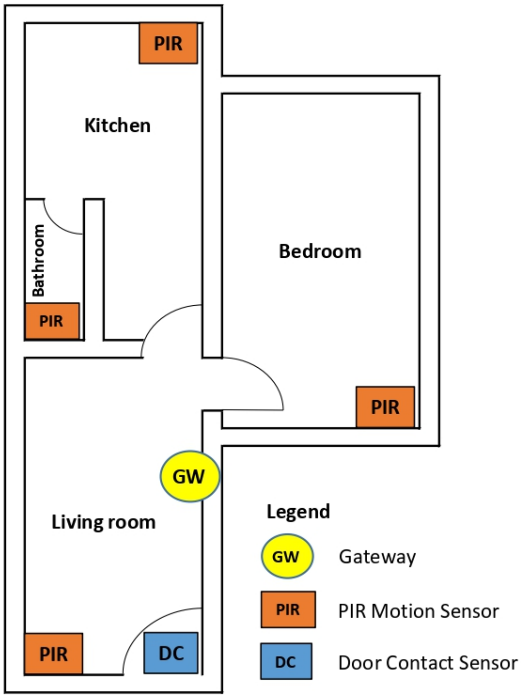

Fig. 2. An illustration of in-home monitoring system in a typical elderly's home.

	device_id	device_loc	gw_timestamp	reading_type	resident_index_list	value
1	6005-m-01	living_room	2018-04-01T00:01:17	motion	MP0012	255
2	6005-m-03	kitchen	2018-04-01T00:02:15	motion	MP0012	255
4	6005-m-04	toilet_bathroom	2018-04-01T00:05:18	motion	MP0012	255
5	6005-m-01	living_room	2018-04-01T00:05:51	motion	MP0012	0
6	6005-m-01	living_room	2018-04-01T00:06:32	motion	MP0012	255
8	6005-m-04	toilet_bathroom	2018-04-01T00:09:18	motion	MP0012	0
9	6005-m-01	living_room	2018-04-01T00:09:40	battery_percent	MP0012	100
10	6005-m-03	kitchen	2018-04-01T00:10:44	battery_percent	MP0012	100

Fig. 3. Example of raw sensor data.

related to sleeping according to the definition given by ICS, and the survey about sleeping habits relates to the sleeping pattern in the month prior to the survey.

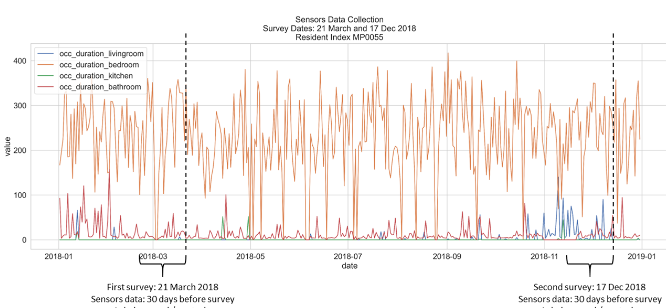

Fig. 4. Sensor data collection timeline.

B. Data Preparation

Data preparation conducted in this study comprised of data cleaning and sleep pattern extraction. During the study duration, i.e., between January 2018 to December 2018, there were 39 active participants, i.e., elderly with in-home monitoring system. Among the 39 elderly who participated in the first survey, 2 elderly did not respond to the survey questions about toileting habits. In addition, 2 elderly had no sensor data from the bathroom motion sensor, and 2 elderly had no sensor data at all in the month preceding the survey. Among the 34 elderly who participated in the second survey, one elderly had a helper or long stay visitor. In addition, 2 elderly had no sensor data from the bathroom motion sensor, and one elderly had no sensor data at all in the month preceding the survey. As both surveys are conducted eight months apart, we treat the survey results from the same elderly as two independent data points in this study. Accordingly, we have 63 data points: 33 data points from the first survey and 30 data points from the second survey. Among them, 46 data points were labeled as nocturia while 27 data points were labeled as normal.

Data cleaning was performed on raw sensor data by removing information other than motion sensors and door contact sensors, for example, information about the battery level of each sensor. As nocturia is defined by the ICS as voiding preceded and followed by night sleeping, a key data preparation step towards deducing nocturia events is to extract the usual night sleeping period of each elderly. In an earlier work [20], this was done by first determining the total active duration of the elderly inside and outside the bedroom, and subsequently estimating the start and end of the sleeping period based on the active duration graphs inside and outside the bedroom (see Fig. 7). However, this works well provided the elderly's sleeping location is in the bedroom, which is not always the case in SHINESeniors.

As such, we propose two additional steps to obtain the usual sleeping location of the elderly during the 30 days prior to the survey before sleep duration extraction. First, we compare the occupancy duration in all rooms during the typical sleeping time (00:00 to 05:00) and designate the location with the highest occupancy duration as the sleeping location for that night. However, if the occupancy duration in all rooms fell below one hour, we consider that the elderly had spent the night outside of home. Next, for the 30 day duration, the most frequently occurring sleep location will be the usual sleep location. These steps are illustrated in Fig. 5 and Fig. 6 for Elderly 1 who sleeps in the bedroom and Elderly 2 who sleeps in the living room.

After the usual sleep location extraction, the sleep period is estimated by finding the left and right peaks of the bowl shape in the graph of total duration in locations other than the usual sleep location. This sleep period is further refined by finding the left and right peaks inside the previous peaks in the graph of active duration in the usual sleep location. Fig. 7 presents the results of the sleep period extraction of Elderly 1 (above) and Elderly 2 (below). The upper graphs are the results of sleep period estimation, while the lower graphs are the results of sleep period refinement. Specifically, the green dashed lines in the upper graphs represent the start and end of the estimated sleep period, and the blue dashed lines in

Fig. 5. Room occupancy duration over 30 days before survey date of Elderly 1 who sleeps in the bedroom (above) and Elderly 2 who sleeps in the living room (below).

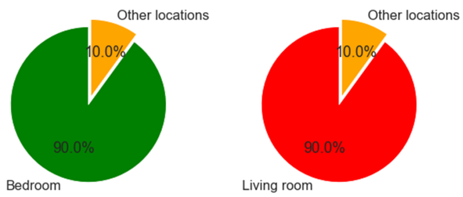

Fig. 6. Usual sleep location of Elderly 1 (left) and Elderly 2 (right).

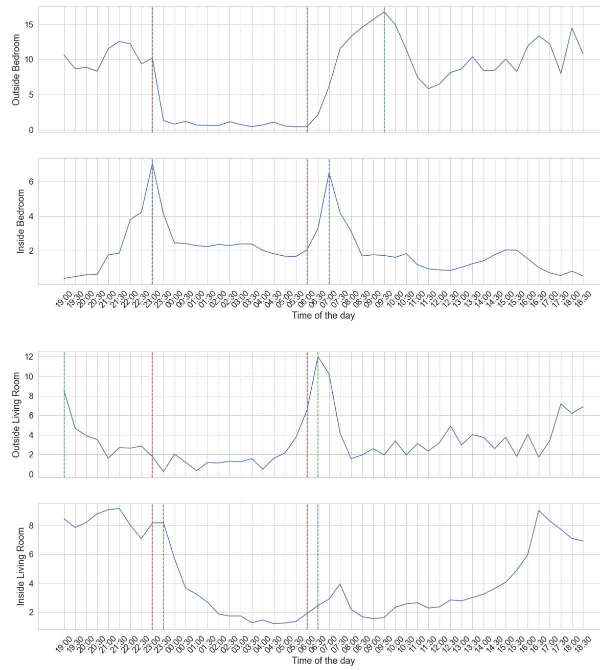

Fig. 7. Sleeping period extraction for Elderly 1 (above) and Elderly 2 (below).

the lower graphs represent the start and end of the refined sleep period. The red dashed lines represent the start and end sleeping period derived from the survey. The results of usual sleeping period extraction from sensor data are similar with results from the survey data, with average differences of 1.6 hours and 1.1 hours in the estimated start and end sleep time, respectively.

C. Feature Extraction

In addition to features such as night sleeping location and duration and voiding visits which are directly related to nocturia, we also extracted other features that depict the elderly's daily living patterns to explore potential correlation with nocturia. These features are defined as follows:

- **Away duration and frequency**: Away duration is calculated when the door contact sensor is triggered, and no motion is detected inside the apartment for a minimum duration of 30 minutes afterwards. Away frequency is the number of times the elderly leaves the apartment.
- **Sleep duration and location**: Sleep duration and location are derived using approaches described in Section III-B.
- **Zonal occupancy and frequency**: The duration spent in each zone of the apartment based on the motion sensor triggered in the respective location. A threshold of two minutes is applied to ensure that the elderly is doing something at that location, and not only passing by. Furthermore, the occupancy frequency is obtained based on the number of times the elderly occupies the respective zone.
- **Zonal active duration**: Activity duration of the elderly based on the firing of the motion sensor in each location. The more active the elderly is in a certain location, the more motion sensor firings there are, and the longer the active duration at that location.
- **In-home transitions**: Number of times the elderly moves from one location to another location in the apartment. For instance, the movement of an elderly from the kitchen to the living room constitutes a single transition. On the other hand, when the elderly goes from the bathroom to the bedroom, she will pass through the kitchen and living room, resulting in a total of three transitions.
- **Voiding**: The number of voiding instances during night time sleep is more straightforward than in the daytime. For instance, while bathroom activity in the middle of night sleeping is very likely voiding, bathroom activity detected during the day can be attributed to washing hands or other activities. A minimum threshold of two minutes is used in the daytime to filter out the activities in the bathroom other than voiding.

We compute each feature for three different sets of durations: (1) *whole day*, (2) *daytime* (7 am to 7 pm), and (3) *night-time* (7 pm to 7 am). For the voiding feature, we additionally divided the night-time into night sleep period and night awake period, such that voiding that occurs during the night sleep period constitutes nocturia. Finally, all features are averaged to a day, to represent the elderly's daily living pattern. This results in a total of 55 sensor-derived features.

Fig. 8 compares the daily nocturia counts extracted from sensor data for 30 days before the survey date between an elderly with nocturia and a normal elderly. It is evident that the actual nocturia count is highly correlated with nocturia labeling based on survey.

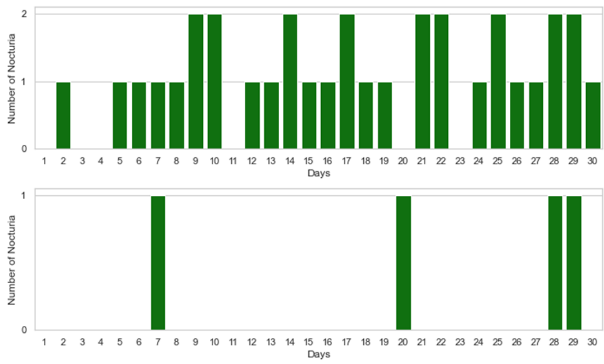

Fig. 8. Sensor-derived nocturia counts during 30 days before survey date of an elderly with (above) and without (below) nocturia.

IV. Sensor-based Nocturia Detection

In this section, based on the nocturia labeling and features extracted, we proceed to build a sensor-based classification model to detect nocturia. We first compute the Pearson Correlation Coefficient (r) between nocturia and each feature, and then removed less important features (r <0.15). Finally, forward feature selection is applied by selecting one feature that results in the highest classification accuracy, and adding more features until there is no further improvement in accuracy.

A. Sensor-based Classification of Nocturia

As observed in Section III-B, several elderly in the SHINESeniors project do not always sleep in the bedroom. As such, apart from the full data set comprising 63 data points from all the elderly (data set A), we considered a subset of elderly who usually sleep in the bedroom (data set B with 54 data points) to evaluate if there is any difference in the classification results. Each data set is randomly split into training and testing set with a proportion of 80:20 respectively. We evaluated the classification performance of four machine learning algorithms, namely, Decision Tree, Support Vector Machine (SVM), K-Nearest Neighbour (KNN) and Naive Bayes. The evaluation metrics used include precision, recall, accuracy and F1-score, where the F1-score will be used as the primary performance metric.

Intuitively, since an elderly is labelled as nocturia if he gets up at least once during the night for voiding (based on his response to the survey), the number of nocturia events as measured by the sensors should be a good proxy for classification. Accordingly, the classification performance for data set A and B is depicted in Table I and II respectively.

For data set A which comprises all elderly, all methods except KNN achieved perfect recall at the expense of lower precision, i.e., all elderly with nocturia are detected, but a few normal elderly are misclassified as nocturia. In terms of F1-score, Naive Bayes and Decision Tree performed the best, followed by SVM and KNN. As evident in Table II, a significant improvement in the classification performance is achieved by removing data points corresponding to elderly sleeping in the living room. All methods, except KNN, achieved the same performance in this case.

TABLE I
Classification results based on number of nocturia events for Data Set A

Methods	TN	FN	FP	TP	Precision	Recall	Accuracy	F1-Score
Decision Tree	1	0	4	8	0.67	1.00	0.69	0.80
SVM	0	0	5	8	0.62	1.00	0.62	0.76
KNN	1	1	4	7	0.64	0.88	0.62	0.74
Naive Bayes	1	0	4	8	0.67	1.00	0.69	0.80

TABLE II
Classification results based on number of nocturia events for Data Set B

Methods	TN	FN	FP	TP	Precision	Recall	Accuracy	F1-Score
Decision Tree	0	0	3	8	0.72	1.00	0.72	0.84
SVM	0	0	3	8	0.72	1.00	0.72	0.84
KNN	0	1	3	7	0.70	0.88	0.63	0.78
Naive Bayes	0	0	3	8	0.72	1.00	0.72	0.84

Next, Table III shows the results of forward feature selection for each data set before the classification. It is interesting to observe that the feature most correlated with nocturia is the bedroom occupancy duration at night for both data sets. In addition, while the number of nocturia events is a contributing feature for data set A, it is not the case for data set B.

TABLE III
Features selected (r value) for data set A and data set B

Data Set A (All Elderly)	Data Set B (Usually sleeps in bedroom)
duration_bedroom_occ_night (0.323)	duration_bedroom_occ_night (0.38)
num_bedroom_occ_night (0.265)	num_toileting_night_awake (0.298)
num_toileting_night_awake (0.265)	duration_act_level_livingroom_night (-0.287)
num_bedroom_occ_wholeday (0.261)	duration_livingroom_occ_day (-0.287)
duration_bedroom_occ_day (-0.135)	duration_away_day (-0.232)
num_nocturia (-0.105)	duration_bedroom_occ_day (-0.201)

Finally, Table IV and Table V show the results of classification with forward feature selection on data set A and data set B using features selected in Table III.

TABLE IV
Classification Results with Forward Feature Selection on Data Set A

Methods	TN	FN	FP	TP	Precision	Recall	Accuracy	F1-Score
Decision Tree	2	0	3	8	0.73	1.00	0.77	0.84
SVM	1	0	4	8	0.67	1.00	0.69	0.80
KNN	0	0	5	8	0.62	1.00	0.62	0.76
Naive Bayes	4	0	1	8	0.89	1.00	0.92	0.94

The improvement in classification performance with forward feature selection is evident by comparing Table IV and V with Table I and II. This implies that daily behavioural patterns other than nocturia events can contribute positively towards nocturia classification. As before, the classification performance for data set B is better than that for data set A owing to the removal of bias due to sleep locations. This is because sleeping occupies a significant portion of time in a

TABLE V
CLASSIFICATION RESULTS WITH FORWARD FEATURE SELECTION ON DATA SET B

Methods	TN	FN	FP	TP	Precision	Recall	Accuracy	F1-Score
Decision Tree	0	1	3	7	0.70	0.88	0.64	0.78
SVM	3	0	0	8	1.00	1.00	1.00	1.00
KNN	0	0	3	8	0.73	1.00	0.73	0.84
Naive Bayes	2	0	1	8	0.89	1.00	0.91	0.94

day, so the difference in sleeping location will affect the value of other features, such as occupancy duration and activity duration in each zone. Henceforth, subsequent analysis on sensor data will focus on data set B, where SVM achieves the best classification performance, followed by Naive Bayes, KNN and Decision Tree.

B. Correlation Analysis between Sensor-derived Features and Nocturia

In this section, we observe the strength and direction of the relationship between nocturia and features extracted from sensors, by calculating the Pearson correlation coefficient (r). Fig. 9 shows the correlation between nocturia and each feature extracted from sensors.

In Fig. 9, we observe that nocturia and sensor-derived features are correlated with various strengths: very weak (r values of 0 to 0.09 or -0.09 to 0), weak (r values of 0.1 to 0.29 or -0.29 to -0.1), and moderate (r values of 0.3 to 0.49 or -0.49 to -0.3). These results support the explanation given by [15] that features extracted from passive data collection (which is our case) may correlate with target diseases, but the strengths are not as significant as features resulting from active data collection which tends to target metrics specific to a disease.

The feature most positively correlated with nocturia is the duration spent by the elderly in the bedroom at night, followed by number of voiding events at night while awake. The feature most negatively correlated with nocturia are the nighttime active duration and daytime occupancy duration in the living room. These findings are consistent with previous studies [11], [26] that have shown that elderly with nocturia tends to have lower energy levels as a result of sleep disturbance. In particular, after each voiding event at night, it is possible that the elderly finds it difficult to fall back to sleep until the next voiding event, resulting in a vicious cycle of disturbed sleep. Beyond correlations with in-home behaviours, nocturia is negatively correlated with the elderly's away duration and frequency. An elderly with nocturia is more likely to prefer to stay home due to low energy level, drowsiness during the day, and the worrisome need to void.

Apart from the positive correlation between nocturia and voiding at night while awake, the results also showed that nocturia is positively correlated with daytime voiding at day and voiding in the middle of sleep. These findings imply that elderly with nocturia tends to urinate more frequently in all time windows. Elderly with nocturia also tends to have higher

Fig. 9. Correlation between Nocturia and Features Extracted from Sensors.

transitions between rooms, which is possibly caused by the frequent need to go to the bathroom for voiding.

Apart from the negative correlation between nocturia and activity level in living room at night, nocturia is also negatively correlated with activity level in living room during the day. Positive correlation between nocturia and activity level in bedroom and bathroom implies that elderly with nocturia tends to spend time in the bedroom rather than perform activities in living room.

V. CORRELATION ANALYSIS BETWEEN NOCTURIA AND OTHER SURVEY FEATURES

In this section, we perform a secondary study to explore potential correlation between nocturia and other survey features with data set A. We first compute the Pearson correlation coefficient between nocturia and survey features related to (i) sleeping habits and (ii) physical and mental conditions of the elderly. The results are shown in Table VI and Table VII respectively.

From Table VI, it is observed that elderly with nocturia are more likely to have trouble getting out of bed in the morning,

TABLE VI
CORRELATION BETWEEN NOCTURIA AND SLEEPING HABITS

Survey Features	Correlation Coefficient
sleep_quality	**-0.107800**
wake_up_because_bad_dreams	-0.095191
actual_sleep_hours	-0.074198
wake_up_because_cannot_breath_comfortably	-0.002063
wake_up_because_feel_too_cold	0.019745
wake_up_because_feel_too_hot	0.025064
wake_up_because_get_up_use_bathroom	0.038566
low_enthusiasm	0.072163
trouble_to_stay_awake_in_activity	0.078704
wake_up_because_have_pain	**0.115768**
nap_duration	**0.144061**
wake_up_because_cough_or_snore	**0.153114**
medicine_to_help_sleep	**0.168232**
cannot_sleep_within_30	**0.191808**
drowsy_during_day	**0.212688**
napping	**0.242306**
time_take_to_sleep	**0.259490**
fall_back_sleep_in_morning	**0.267943**
trouble_get_out_of_bed_in_morning	**0.277657**

TABLE VII
CORRELATION BETWEEN NOCTURIA WITH PHYSICAL AND MENTAL CONDITIONS

Survey Features	Correlation Coefficient
glaucoma	**-0.237888**
ability_to_perform_daily_living	**-0.178845**
high_cholesterol	-0.028318
other_heart	0.010410
diabetes	0.012089
high_blood_pressure	0.045589
number_of_chronical_diseases	0.090972
kidney	**0.107264**
depression_score	**0.107935**
respiratory	**0.108447**
cancer	**0.108895**
fractures	**0.109629**
cerebrovascular	**0.110363**
digestive	**0.111098**
chronic_back_pain	**0.111098**
osteoporosis	**0.111544**
other_fractures	**0.133352**
heart_attack	**0.137778**
cataract	**0.142282**
joint_pain	**0.162163**

and are more likely to fall back asleep in the morning. They are also more likely to feel drowsy and hence have longer naps during the day. At night, they tend to take a while (30 minutes or longer) and sometimes require medication to help them fall asleep. Their sleep is likely to be disturbed due to coughing, snoring or pain. These findings are consistent with other findings in previous studies [11], [26].

From Table VII, we observe an interesting finding that glaucoma is negatively correlated with nocturia. As elderly with glaucoma have limited visual abilities, they are more likely to use adult diapers so that they do not have to go to the bathroom in the middle of night sleeping. In addition, it is observed that elderly with nocturia are likely to have more chronic conditions than normal elderly. Specifically, they are likely to suffer from conditions related to physical frailty such as joint pains, fractures, osteoporosis, chronic back pains, and therefore are less able to perform activities of daily living. To further validate this observation, we tabulate the number of nocturia and normal elderly who responded positively to frailty-related survey attributes in Table VIII. This confirms our observation that elderly with nocturia are more likely to experience events linked to frailty, which is consistent with previous studies [3], [11].

TABLE VIII
COMPARISON OF THE NUMBER OF NOCTURIA AND NORMAL ELDERLY WHO RESPONDED POSITIVELY TO FRAILTY-RELATED SURVEY ATTRIBUTES

Frailty Attribute	Nocturia	Normal
Fatigue	29	12
Resistance	18	4
Ambulation	20	10
Illnesses	35	12
Weight Loss	6	3
Total Illnesses more than 2	19	6
Fallen Events	11	5

VI. CONCLUSION

In this study, we used passive, in-home monitoring to detect the presence of nocturia among 39 community-dwelling elderly living alone, where nocturia labeling was done based on psychosocial surveys administered at two time points 8 months apart. Based on objective and continuous data from motion sensors in each room of the apartment and a contact sensor on the main door up to one month prior to each survey, we first extracted 55 features consisting of daily behavioural patterns of the elderly, such as room occupancy, activity level in each room, and going out duration. Subsequently, we derived a sensor-based nocturia classification model, and compared the performance of four machine learning algorithms based on (i) number of nocturia events alone, (ii) features selected using forward feature selection, and (iii) filtering by the usual sleeping location of the elderly.

The results showed several interesting findings: (i) classification using number of nocturia events alone achieved perfect recall at the expense of lower precision, (ii) classification using forward feature selection improved classification performance compared to using number of nocturia events alone, (iii) classification performance by using usual sleep location as an additional feature performed better owing to the removal of bias due to sleep locations, and (iv) perfect accuracy can be achieved with the Support Vector Machine based classification model in combination with forward feature selection and filtering by usual sleep location.

In addition, correlation analysis between nocturia and features extracted from sensors revealed that elderly with nocturia (i) tend to spend time in the bedroom rather than performing activities in other rooms, (ii) leave the bedroom usually for urinating in the bathroom, and (iii) rarely leave their homes. Further analysis on the survey findings also revealed that elderly with nocturia are more likely to have poor sleep quality, resulting in daytime drowsiness, low enthusiasm, and difficulty in getting out of bed in the morning. They are also more likely to suffer from conditions related to physical frailty. The above results lend support for further research on passive in-home monitoring as a digital biomarker for detection of nocturia and related conditions in live-alone elderly.

Acknowledgment

This research was supported by the iCity Lab, a partnership between Tata Consultancy Services (TCS) and Singapore Management University (SMU). SHINESeniors is a Singapore Management University led research project supported by the Singapore Ministry of National Development and National Research Foundation under the Land and Livability National Innovation Challenge (L2NIC) Award No. L2NICCFP1-2013-5.

References

[1] Paul Abrams, Linda Cardozo, Magnus Fall, Derek Griffiths, Peter Rosier, Ulf Ulmsten, Philip Van Kerrebroeck, Arne Victor, and Alan Wein. The standardisation of terminology in lower urinary tract function: report from the standardisation sub-committee of the international continence society. *Urology*, 61(1):37–49, 2003.

[2] Arnav Agarwal, Leyla N Eryuzlu, Rufus Cartwright, Kristian Thorlund, Teuvo LJ Tammela, Gordon H Guyatt, Anssi Auvinen, and Kari AO Tikkinen. What is the most bothersome lower urinary tract symptom? individual-and population-level perspectives for both men and women. *European urology*, 65(6):1211–1217, 2014.

[3] Wendy F Bower, D Michael Whishaw, and Fary Khan. Nocturia as a marker of poor health: causal associations to inform care. *Neurourology and urodynamics*, 36(3):697–705, 2017.

[4] Sara T Brookes, Jenny L Donovan, Melissa Wright, Simon Jackson, and Paul Abrams. A scored form of the bristol female lower urinary tract symptoms questionnaire: data from a randomized controlled trial of surgery for women with stress incontinence. *American journal of obstetrics and gynecology*, 191(1):73–82, 2004.

[5] Fong-Ying Chen, Yu-Tzu Dai, Chih-Kuang Liu, Hong-Jeng Yu, Cheng-Ying Liu, and Tony Hsiu-Hsi Chen. Perception of nocturia and medical consulting behavior among community-dwelling women. *International Urogynecology Journal*, 18(4):431–436, 2007.

[6] Yong Sun Choi, Joon Chul Kim, Young Ho Kim, Jong Bo Choi, Won Hee Park, and Dong Hwan Lee. Classification of nocturia by analyzing frequency volume chart and relations with international prostate symptom score in male patients with lower urinary tract symptoms in korea. *Investigative and Clinical Urology*, 60(4):267–274, 2019.

[7] JL Donovan, TJ Peters, P Abrams, ST Brookes, JJMCH De La Rosette, and W Schäfer. Scoring the short form icsmalesf questionnaire. *The Journal of urology*, 164(6):1948–1955, 2000.

[8] Nadee Goonawardene, Hwee-Pink Tan, and Lee Buay Tan. Unobtrusive detection of frailty in older adults. In *International Conference on Human Aspects of IT for the Aged Population*, pages 290–302. Springer, 2018.

[9] Nadee Goonawardene, XiaoPing Toh, and Hwee-Pink Tan. Sensor-driven detection of social isolation in community-dwelling elderly. In *International Conference on Human Aspects of IT for the Aged Population*, pages 378–392. Springer, 2017.

[10] Kouhei Hisamori, Takeshi Abe, Yoshikazu Maekawa, Yoko Akiyama, Fumihito Mishima, Kenji Yamada, and Shigehiro Nishijima. Study on measurement of water content in human body by impedance method. In *2010 World Automation Congress*, pages 1–6. IEEE, 2010.

[11] Tove Holm-Larsen. The economic impact of nocturia. *Neurourology and urodynamics*, 33(S1):S10–S14, 2014.

[12] Amy Hsu, Sanae Nakagawa, Louise C Walter, Stephen K Van Den Eeden, Jeanette S Brown, David H Thom, Sei J Lee, and Alison J Huang. The burden of nocturia among middle-aged and older women. *Obstetrics and gynecology*, 125(1):35, 2015.

[13] Verena Huppert, Jan Paulus, Ute Paulsen, Martin Burkart, Bernd Wullich, and Bjoern M Eskofier. Quantification of nighttime micturition with an ambulatory sensor-based system. *IEEE journal of biomedical and health informatics*, 20(3):865–872, 2015.

[14] So Young Kim, Woojin Bang, Min-Su Kim, Bumjung Park, Jin-Hwan Kim, and Hyo Geun Choi. Nocturia is associated with slipping and falling. *PloS one*, 12(1):e0169690, 2017.

[15] Lampros C Kourtis, Oliver B Regele, Justin M Wright, and Graham B Jones. Digital biomarkers for alzheimer's disease: the mobile/wearable devices opportunity. *NPJ digital medicine*, 2(1):1–9, 2019.

[16] Varant Kupelian, Mary P Fitzgerald, Steven A Kaplan, Jens Peter Norgaard, Gretchen R Chiu, and Raymond C Rosen. Association of nocturia and mortality: results from the third national health and nutrition examination survey. *The Journal of urology*, 185(2):571–577, 2011.

[17] Varant Kupelian, John T Wei, Michael P O'Leary, Jens Peter Norgaard, Raymond C Rosen, and John B McKinlay. Nocturia and quality of life: results from the boston area community health survey. *European urology*, 61(1):78–84, 2012.

[18] Jane T Kurtzman, Ari M Bergman, and Jeffrey P Weiss. Nocturia in women. *Current Opinion in Urology*, 26(4):315–320, 2016.

[19] BAI Liming, Alex Ishiwata Gavino, Pius Lee, Kim Jungyoon, Liu Na, Tan Hwee Pink Pi, Tan Hwee Xian, Tan Lee Buay, Toh Xiaoping, Alvin Valera, et al. Shineseniors: personalized services for active ageing-in-place. In *2015 IEEE First International Smart Cities Conference (ISC2)*, pages 1–2. IEEE, 2015.

[20] Xiaoping Ma, Nadee Goonawardene, and Hwee Pink Tan. Identifying elderly with poor sleep quality using unobtrusive in-home sensors for early intervention. In *Proceedings of the 4th EAI International Conference on Smart Objects and Technologies for Social Good*, pages 94–99, 2018.

[21] P Miranda Ede, CM Gomes, FC Torricelli, and J de Bessa. Júnior, de castro je, ferreira br, et al. *Nocturia is the lower urinary tract symptom with greatest impact on quality of life of men from a community setting. Int Neurourol J*, 18:86–90, 2014.

[22] Matthias Oelke, Peter Anderson, Robert Wood, and Tove Holm-Larsen. Nocturia is often inadequately assessed, diagnosed and treated by physicians: results of an observational, real-life practice database containing 8659 european and us-american patients. *International journal of clinical practice*, 70(11):940–949, 2016.

[23] Matthias Oelke, Birgitt Wiese, and Richard Berges. Nocturia and its impact on health-related quality of life and health care seeking behaviour in german community-dwelling men aged 50 years or older. *World journal of urology*, 32(5):1155–1162, 2014.

[24] Plácido Rogério Pinheiro, Isabelle Tamanini, Mirian Caliope Dantas Pinheiro, and Victor Hugo C De Albuquerque. Evaluation of the alzheimer's disease clinical stages under the optics of hybrid approaches in verbal decision analysis. *Telematics and Informatics*, 35(4):776–789, 2018.

[25] Georg Schatzl, Christian Temml, Jörg Schmidbauer, Brigitte Dolezal, Gerald Haidinger, and Stephan Madersbacher. Cross-sectional study of nocturia in both sexes: analysis of a voluntary health screening project. *Urology*, 56(1):71–75, 2000.

[26] I-Hung Shao, Chia-Chen Wu, Hueih-Shing Hsu, Shyh-Chyi Chang, Hsu-Hsiang Wang, Heng-Chang Chuang, and Yuan-Yun Tam. The effect of nocturia on sleep quality and daytime function in patients with lower urinary tract symptoms: a cross-sectional study. *Clinical interventions in aging*, 11:879, 2016.

[27] Satetha Siyang, Chatchawal Wongchoosuk, and Teerakiat Kerdcharoen. Diabetes diagnosis by direct measurement from urine odor using electronic nose. In *The 5th 2012 Biomedical Engineering International Conference*, pages 1–4. IEEE, 2012.

[28] Yasuharu Tabara, Takeshi Matsumoto, Kimihiko Murase, Kazuya Setoh, Takahisa Kawaguchi, Shunsuke Nagashima, Shinji Kosugi, Toyohiro Hirai, Takeo Nakayama, Tomoko Wakamura, et al. Frequent nocturnal urination in older men is associated with arterial stiffness: The nagahama study. *Hypertension Research*, 42(12):1996–2001, 2019.

[29] Carla Taramasco, Tomas Rodenas, Felipe Martinez, Paola Fuentes, Roberto Munoz, Rodrigo Olivares, Victor Hugo C Albuquerque, and Jacques Demongeot. A novel low-cost sensor prototype for nocturia monitoring in older people. *IEEE Access*, 6:52500–52509, 2018.

[30] Philip Van Kerrebroeck, Paul Abrams, David Chaikin, Jenny Donovan, David Fonda, Simon Jackson, Poul Jennum, Theodore Johnson, Gunnar Lose, Anders Mattiasson, et al. The standardisation of terminology in nocturia: report from the standardisation sub-committee of the international continence society. *Neurourology and urodynamics*, 21(2):179–183, 2002.

[31] Camille P Vaughan, Constance H Fung, Alison J Huang, Theodore M Johnson 2nd, and Alayne D Markland. Differences in the association of nocturia and functional outcomes of sleep by age and gender: a cross-sectional, population-based study. *Clinical therapeutics*, 38(11):2386–2393, 2016.

[32] Tomonori Yamanishi, Miki Fuse, Chiharu Yamaguchi, Tomoyuki Uchiyama, Takao Kamai, Shinsuke Kurokawa, and Tatsuo Morita. N octuria q uality-of-l ife questionnaire is a useful tool to predict nocturia

and a risk of falling in j apanese outpatients: A cross-sectional survey. *International Journal of Urology*, 21(3):289–293, 2014.