Wearable Monitoring for the Detection of Nocturnal Agitation in Dementia

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Abstract: Nocturnal agitation is one of the symptoms exhibited by dementia patients. Diagnosing and monitoring the evolution of agitation is difficult because patient monitoring requires a doctor, nurse or caregiver observing patients for extended periods of time. In this work, we propose to use an automatic monitoring system based on wearable technology that complements the caregiver's work. The proposed system uses a wrist wearable device to record agitation data, which are subsequently classified through machine learning techniques as quantifiable indexes of nocturnal agitation. Preliminary tests performed with volunteers showed that the classification of recorded movements between nocturnal agitation or quiet periods was successful in 78.86% of the cases. This proof of concept demonstrates the feasibility of using wearable technology to monitor nocturnal agitation.

1 INTRODUCTION

According to recent studies, 35.6 million people lived with dementia worldwide in 2010, and estimations predict that these numbers will almost be doubled every 20 years, 65.7 million living with dementia in 2030 and 115.4 million living with dementia in 2050 (Prince et al., 2013). Approximately one-quarter of adults with Alzheimer's disease (AD) and with other dementias suffer from sleep disturbances (Rose et al., 2010).

Patients with dementia usually present sleep disturbances such as insomnia, sleep disruption, or movements that can escalate to become agitation. The treatment of these disturbances is complex because they involve multiple factors, such as neurodegenerative changes in the brain, the patient's environment, medical or psychiatric morbidity, and medications used to treat chronic illnesses and dementia-related behavioral symptoms (Deschenes and McCurry, 2009).

In particular, changes in nocturnal agitation behaviors may provide information about the evolution of dementia. However, it is difficult to get objective and quantifiable information about the nocturnal behavior of dementia patients because they are not usually aware of their behavior and their caregivers cannot monitor them 24 hours a day (Cooke and Ancoli-Israel, 2006).

Nocturnal agitation is generally assessed using observational scales, such as the Cohen-Mansfield Agitation Inventory (CMAI) (Cohen-mansfield et al., 1989), which is particularly difficult to apply in out-of-hospital settings. This work presents the first steps towards a pervasive health tool for automatically monitoring nocturnal agitation. In order to detect the nocturnal activity, we propose a system based on wearable wristband computers similar to watches because most patients feel comfortable using them. Then, the collected data is analyzed using machine learning techniques. In particular, Support Vector Machines (SVMs), which are widely used for mining physiological data in medical applications (Banaee et al., 2013), are used to identify nocturnal abnormal behaviors by classifying movements as normal or agitated. The aim of this work is to provide an objective and quantifiable characterization of nocturnal movements to help medical staff in their diagnosis.

The remainder of this article is organized as follows. Section 2 summarizes related work. Section 3 describes the development of the proposed system: selection of the wearable device, creation of the reference dataset, and classification algorithm. Finally, in

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Section 4 and Section 5, we present and discuss the results respectively.

2 RELATED WORK

Our approach is based on two main aspects: the use of wearable technology to characterize movement through collected accelerometer data, and the use of machine learning techniques to detect nocturnal agitation as a complementary diagnostic tool.

Several works focus on studying the feasibility of replacing traditional monitoring and diagnostic systems by less intrusive and more reliable ones in the case of dementia patients. In (Ancoli-Israel et al., 1997) and (Van Someren, 1997), actigraphy is a medium to collect objective sleep data. However, neither one focuses on nocturnal agitation which is a specific symptom of dementia sleep activity (Sink et al., 2005).

Other works focus on detecting nocturnal agitation of patients with dementia, but they tend to present complex multi-sensor systems. In (Sakr et al., 2010), the agitation is detected using a heart rate sensor, a galvanic skin response sensor and a skin temperature sensor. In (Fook et al., 2007), the authors propose a video camera for detecting agitated behavior. In (Biswas et al., 2006), the system used to detect agitation is composed by acoustic sensors, pressure sensors and ultrasound sensors.

In contrast to previous studies, in this work we propose a simple system using only accelerometer to quantify nocturnal agitation in dementia. Accelerometer measures have been found to correlate well with the CMAI scale (Nagels et al., 2006), so our hypothesis is that accelerometry can be a simple and low-cost solution for detecting agitation in patients with dementia.

3 METHODS

To assess the viability of using wearable accelerometer device for nocturnal agitation monitoring, we designed a three-phase proof of concept. During the first phase we studied the wearable accelerometer devices available in market and their features taking into account the needs of our research. The second phase consisted on the creation of the reference dataset, which involved the definition of the experimental protocols, the recruitment of participants, and the recording of data. Finally, the third phase consisted on the selection and application of a classification algorithm in order to extract useful information about nocturnal agitation.

3.1 Technological Survey

Nowadays, there is a great diversity of wearable devices in the market, and they will continue to grow (Intelligence, 2015). Their functionality opens a wide range of possibilities; phone calls, activity monitoring and geolocation are some of the most common features of these devices. Unfortunately, most commercial devices do not allow access to raw data. Popular devices such as Jawbone, Misfit, Fitbit or Garmin trackers use proprietary algorithms to translate the raw data into generic activity statistics, and their accuracy against gold standard methods remains understudied (Kolla et al., 2016). Even if they were accurate enough, generic activity measures such as number of steps or hours of sleep may not necessarily be the best surrogate for nocturnal agitation.

Thus, in order to find the most appropriate wearable device for our research we considered only those devices that allowed access to raw data. In addition to that, we considered additional features. Since the agitation is characterized for a restlessness state and movements with different intensity degree, a 3-axis accelerometer was considered to be the most appropriate sensor to measure the periods and the intensity of the movements.

Another feature required in the device is a sampling rate greater or equal than 20 Hz, since the fastest body movements, such as spasms and tremor, are in the order of 10 Hz (Bendersky et al., 2014). Other desirable characteristics are offline data storage capabilities, exportable data in standard format, and low cost. The memory has to be able to store the activity of a complete night, so the device logging period needs to be at least 8 hours at 20 Hz. The possibility of exporting data in a standard format is an advantage because it can be used easily as input data for statistical tools, signal processing tools or simulation tools. Finally, in 2010, the total estimated worldwide costs of dementia were US$604 billion (Wimo et al., 2013), so cost-effective monitoring systems would help reduce that cost.

Taking into account all of those requirements, we selected Original GENEActiv by Activeinsights whose sampling frequency range is 10-100Hz, its maximum logging period is 22 days @ 20Hz, its exporting formats are BIN (Binary file) and CSV (Comma-separated values), and its cost includes GENEActiv software.

3.2 Creation of the Reference Dataset

In order to develop and validate the classification algorithm, a reference dataset was created by recording controlled movements imitating nocturnal agitation and quiet periods in a realistic way.

3.2.1 Protocols

In order to understand the real behavior of dementia patients, we had the cooperation of a medical advisor, the responsible of the Geriatrics Department of the Hospital San Juan de Dios, Zaragoza, Spain. She described for us the usual movements of dementia patients when the night is quiet, agitated or with insomnia.

Taking into account these descriptions, we defined the movements to be performed by our test subjects (see Tables 1 and 2). The result was reviewed and approved by the medical advisor, who confirmed that the movements closely resembled the nocturnal agitation movements found in dementia patients. Two protocols were defined for subjects to follow during the tests. The first protocol contained movements of the extremities, and the second protocol contained movements with the whole body.

Table 1: Protocol P1. Movements of the extremities and their duration.

Duration	Movement
15 s.	Remain laying down
10 s.	Move right arm from bottom to top
15 s.	Remain laying down
10 s.	Move left arm from bottom to top
15 s.	Remain laying down
10 s.	Try to sit up
15 s.	Remain laying down
10 s.	Move right leg from bottom to top
15 s.	Remain laying down
10 s.	Move left leg from bottom to top
15 s.	Remain laying down
15 s.	Stand up and walk
5 s.	Move the wearable device on your wrist

Table 2: Protocol P2. Movements of the whole body and their duration.

Duration	Movement
15 s.	Remain laying down
10 s.	Sit up on the bed
15 s.	Remain laying down
10 s.	Laying put in bed
15 s.	Remain laying down
10 s.	Try to sit up
15 s.	Remain laying down
10 s.	Stand up
15 s.	Remain laying down
10 s.	Walk

3.2.2 Recruitment of Volunteers and Data Recording

Eleven healthy volunteers participated in the experiments, 4 females (mean age 35.5 years, SD 5.17) and 7 males (mean age 30.6 years, SD 9.29). All volunteers signed informed consent.

Tests were conducted in a sleep lab that is specially equipped for medical and nursing students (Figure 1). Therefore, volunteers posed as patients in the hospital beds available in this room. Most patients with dementia are elderly, whose movements are limited not only by the illness, but also by age. For this reason, participants wore 1.5 kg weights on their ankles and wrists to limit their movements, in order to simulate a real scenario as far as possible. Figure 1 shows a volunteer on the hospital bed waiting to start the tests.

Figure 1: Volunteer with weights in his extremities on a hospital bed.

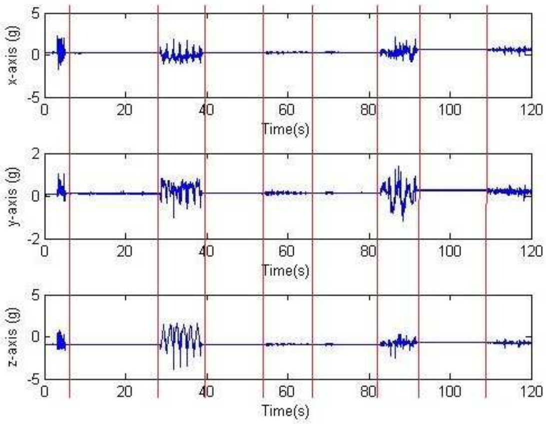

Figure 2: Segment of accelerometry traces recorded during protocol P1. Vertical lines indicate the division between movements and quiet periods.

Participants performed the movements in protocols P1 and P2. Accelerometry data was recorded by the wearable accelerometer device. Both protocols could be correctly executed, recorded and stored in 8 out of the 11 cases. Figure 2 shows a segment of recorded data.

3.2.3 Signal Processing

To classify the movements of the recorded dataset into agitated periods and normal/quiet periods, we used Support Vector Machines (SVMs) following the guidelines provided in (Hsu et al., 2008). The first step was to define the features to be fed to the SVM classifier. These features have to be representative of the quiet and agitation periods based on available measurements (Guyon et al., 2006). Classical signal processing techniques were applied to compute the features as follows.

Acceleration on x, y and z axes was recorded at a sampling frequency of 100 Hz. Recordings were processed in segments from 5 to 15 s., depending on the duration of the movement as specified in the protocol. In order to eliminate the effect of gravity, the mean acceleration on each axis was subtracted from its corresponding trace. Then, traces were low-pass filtered with a cut-off frequency of 10 Hz. The resulting traces, denoted as a_x, a_y, a_z, where used to compute the classification features as follows. For axis $i = x, y, z$ the following features were computed:

- Peak acceleration

$$A_i = \max(a_i) \tag{1}$$

- Energy

$$E_i = \sum_{n=1}^{N} |a_i(n)|^2 \tag{2}$$

where n indicates the sample within the trace.

- Peak amplitude of the frequency spectrum

$$S_i = \max(FFT(a_i)) \tag{3}$$

where FFT stands for Fast Fourier Transform.

- Peak frequency, F_i, computed as the frequency corresponding to S_i.
- Relative peak amplitude, R_i, computed as the difference between S_i and the mean amplitude of the spectrum between 9 and 10 Hz.

Furthermore, the modulus of the acceleration vector was computed as $m = \sqrt{a_x^2 + a_y^2 + a_z^2}$, and the same features as in S_i, F_i and R_i were computed from m, thus obtaining features S_m, F_m and R_m.

As a result, we obtained a set of 18 features that contained information about the amplitude and temporal variations of the wrist acceleration.

3.2.4 Feature Selection

In order to perform a selection of the most relevant features for agitation detection, the 18 extracted features were divided in 3 sets:

- Temporal Axis Features (TAF): A_i and E_i where $i = x, y, z$.
- Frequency Axis Features (FAF): S_i, F_i and R_i where $i = x, y, z$.
- Frequency Modulus Features (FMF): S_m, F_m and R_m.

The possible combinations (see Table 3) of these sets were evaluated using cross-validation in order to find which ones contain relevant, irrelevant or redundant information for agitation detection.

Table 3: Sets of features resulting of the extracted features combination. The combination depends on the processing signal: temporal or frequency axis, and, single axis signal or modulus signal.

Feature Set	Combinations
B_1	TAF
B_2	FAF
B_3	FMF
B_4	TAF & FAF
B_5	TAF & FMF
B_6	FAF & FMF
B_7	TAF & FAF &FMF

3.2.5 Classification of Movements

Following the guidelines in (Burges, 1998; Hsu et al., 2008), movements were classified following the next steps: division of the data in training and testing subsets, transformation of movement data into SVM package format, scaling data, selection of a kernel function, search of the optimum parameters using cross-validation, and training and testing the data.

The reference dataset was divided in two subsets, one for training and one for testing. Knowing that the imbalanced datasets where the number of negative instances far outnumbers the positive instances declines the performance of SVM significantly (Wu and Chang, 2003), the division was made at 50%, that is, the recordings of four volunteers (50%) were used for training and the rest were used for testing. On each subset, the number of agitated movements (positive instances) was similar to the number of normal movements/quiet periods (negative instances) (Table 4).

Table 4: Number of agitated and normal/quiet movements that compose the dataset of protocol P1 and protocol P2.

		Protocol P1	Protocol P2
Training	Agitation	48	37
	Normal	50	24
Testing	Agitation	48	40
	Normal	50	32

For each instance, a instance-label pair is defined as (x_i, y_i) $i = 1, \ldots, n$ where $x_i \in R^n$ is the instance with feature values for a movement, and $y_i \in \{+1, -1\}$ is a label that determines the class of x_i, negative or positive instance. Given the instance-label pairs for a subset, the Support Vector Machine (SVM) (Cortes and Vapnik, 1995) can be expressed as the following optimization problem:

$$\min_{w,b,\xi} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \xi_i, \tag{4}$$

$$\text{subject to } y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i, \tag{5}$$

$$\xi_i \geq 0, \tag{6}$$

where w and b define the separating hyper plane, ξ_i are 'slack' variables which allow for misclassified vectors and ϕ is a function that maps the training vectors x_i into a higher dimensional space.

Scaling avoids that greater numeric ranges take precedence over smaller ones. At the same time, numerical difficulties during the calculation are decreased (Sarle et al., 1997). For these reasons, instances were scaled to [-1,1]. On the other hand, a kernel function $K(x_i, x_j) = \phi(x_i) \cdot \phi(x_j)$ can be used to avoid the explicit definition of a mapping function ϕ. The Radial Basis Function (RBF) is the kernel used in this work, defined as:

$$K(x_i, x_j) = \exp(-\gamma ||x_i - x_j||^2), \quad \gamma > 0. \tag{7}$$

A RBF kernel improves classification results over a linear kernel in most cases (Chang and Lin, 2011), but it's necessary to select suitable values for γ and C parameters. In order to find the optimum values, a grid-search was carried out by creating a grid space of (C, γ) pairs with $\log_2 C \in -5, -4, \ldots, 15$ and $\log_2 \gamma \in -15, -14, \ldots, 3$. For each pair (C, γ) in the space, we performed a five-fold cross validation (CV) on each training subset B_i. The pair (C, γ) for each set B_i is chosen taking into account the maximum mean CV accuracy.

Each selected pair (C_i, γ_i) together with the training subset B_i, where $i = 1, .., 7$, are used to create a SVM classifier. Then, testing subsets B_i were classified using the corresponding classifier i.

4 RESULTS

The optimum RBF parameters found during the grid search are presented in Table 5. Taking into account the results of Table 5, the feature set B_2 is the most relevant when all movements are evaluated together.

The classification results were evaluated by comparing the accuracy (Acc), which is the percentage of instances correctly classified, the sensitivity (Se), which is the percentage of positive instances correctly classified, and the specificity (Sp), which is the percentage of negative instances correctly classified. Table 6 presents the classification results in testing sets.

The maximum accuracy for movements in protocol P1 is 69.90% for feature set B_2. In contrast, the feature sets B_1, B_6 and B_7 returned the best accuracy, 94.44% for movements in protocol P2. And the union of both protocols returns 78.86% of accuracy in feature sets B_2 and B_6.

5 DISCUSSION AND CONCLUSIONS

In this study, we analyzed nocturnal agitation using a wearable device and machine learning techniques. Results showed that nocturnal agitation movements

Table 5: Optimization parameters for RBF-SVM obtained with the whole training set (protocols P1 and P2). The accuracy (%) resulting from cross-validation is reported as mean ± standard deviation.

Feature Set	Accuracy (%)	log_2C	$log_2\gamma$
B_1	78.67 ± 7.98	4	-2
B_2	79.23 ± 7.88	12	3
B_3	74.84 ± 4.43	2	-5
B_4	74.84 ± 6.26	12	3
B_5	78.45 ± 8.11	4	1
B_6	77.42 ± 10.07	14	4
B_7	76.09 ± 5.73	15	5

Table 6: RBF-SVM classification results for the testing set. For each B_i, C and γ were set as in Table 5 for the SVM. Se: Sensitivity, Sp: Specificity, Acc: Accuracy.

Feature Set	P1			P2			P1&P2		
	Se (%)	Sp (%)	Acc (%)	Se (%)	Sp (%)	Acc (%)	Se (%)	Sp (%)	Acc (%)
B_1	45.83	67.27	57.28	100.0	87.50	94.44	70.45	77.01	73.71
B_2	52.08	85.45	69.90	90.00	78.13	84.72	62.50	95.00	78.86
B_3	68.58	34.55	48.54	100.0	28.13	68.06	82.95	40.23	61.71
B_4	35.42	90.91	65.05	97.50	59.38	80.56	54.55	93.10	73.71
B_5	27.08	81.82	56.31	82.50	90.63	86.11	59.09	87.36	73.14
B_6	50.00	81.82	66.99	95.00	93.75	94.44	69.32	88.51	78.86
B_7	58.33	77.55	66.99	97.56	90.63	94.44	56.82	90.80	73.71

can be successfully detected with an accuracy of 78.86%. Classification results were better for protocol P2 than for protocol P1 or for the whole dataset. Protocol P1 involves some movements that are difficult to detect using the wearable device on a wrist, such as *move the legs*, or movements that can be easily confused with agitation although they are normal, such as *move the clock*. On the other hand, protocol P2 contains more energetic movements, which are easier to classify. The applicability of these results to real settings will depend on the realism of the simulated movements. The protocols described here included clearly defined movements, with obvious differences between agitation and normal/quiet periods. An evolution of the system should be trained with more realistic protocols, which could include movements such as *roll over the bed* or *cover with bed sheets*. These movements are more complex than *remain laying down* and they introduce a greater confusing factor, but at the same time they may better reflect actual nocturnal behavior.

Although preliminary results are promising, several limitations of the work need to be acknowledged. First, the use of different kernel functions could be explored, in order to find a classifier with better results, or to confirm that the radial basis function is the best for this particular classification problem. Also, by comparing the results of table 6, the relevance of frequency features over temporal features is clear, since the best results for the whole dataset correspond to B2 and B6 feature sets. These feature sets only contain frequency features, and the main difference between both is the modulus features. B6 contains all the features of B2 more the frequency features of the modulus signal. While the B2 feature set increases the accuracy of protocol P1 up to 69.90%, the accuracy of protocol P2 is increased by the B6 feature set up to 94.44%. Thus, modulus features include relevant information to classify movements in protocol P2, but some of the modulus features may include redundant information for the classification of movements in protocol P1. The inclusion of more sophisticated feature selection methods may result in a net improvement of the solution.

The presented proof of concept was designed in coordination with medical staff in order to study the feasibility to improving dementia diagnostics by using wearable devices. Since the preliminary results demonstrated that it is possible to detect agitation using a wearable accelerometer, the next step towards clinical translation of our research will be to perform a pilot study with hospitalized patients, after including the above mentioned classification improvements.

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