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An advanced Nursing homes activity tracking for Elderly Care support

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Abstract:

A lot of nursing home residents suffer health issues such as pressure ulcers, night walking and incontinence. Previous research shows that these issues have a clear link with motion patterns of patients during bedtime. This paper examines if unobtrusive activity tracking can be done in the bed via accelerometers on the mattress. We show that, with enough training on accelerometer data from variable conditions, a high accuracy can be achieved.

Keywords: CNN, Elderly Care, Incontinence, Machine Learning, Nursing homes

1. INTRODUCTION:

Nursing home residents often suffer from health issues during bedtimes such as pressure ulcers, incontinence, and night-time wandering. These health issues not only affect the resident itself but also burdens the care personnel with an increased workload. Preventing these health issues would relieve the pressure and increase the well-being of residents. Human activity tracking has proven to be an effective way to detect and aid with such health issues. Data from a previous study showed that sensors attached to the mattress can indicate bed movements. [1]

More than 50% of the residents in long-term care settings experience incontinence [2]. Previous studies have explored how sleep agitation and incontinence events are correlated. These studies show that around half (49%) of the incontinence events are proceeded or succeeded by agitation [3]. Half of those happened before the wetness event and the other half directly after the wetness event, showing that there is a correlation between agitation and incontinence.

Pressure over longer periods in the same body area can result in pressure-ulcers. Current research also suggests that also pressure ulcers are very common in nursing homes, with incident rates ranging from 8.8% to 29.9%. The healing of each of these pressure ulcers per day is estimated to cost between €1.71 - €470.49 dependent on the severity of the ulcer (four stages). [4] An ulcer with a mild severity (stage 1-2 will heal within weeks). More severe ulcers on the other hand can take months until they are fully healed. Prevention of these ulcers would significantly lower these costs and increase the well-being of the resident. The best preventive measures consist of removing or redistributing the pressure in these areas of the body. The study in [5] showed that a two-hour repositioning interval should be the minimum for patients at risk.

Accordingly, in recent years, a lot of research has been done to do activity recognition, e.g. to do sleep quality prediction [6]. However, these approaches use worn sensors, which could be obtrusive and annoying for the user. Some other studies have used body-worn accelerometers to do activity recognition via a wearable [7] or a

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smartphone [8]. Most of these studies use deep learning approaches, such as a Convolutional Neural Network (CNN) to classify the movements. Other conventional approaches manually extract features and select few to further use them for classification. This latter method has proven to be less efficient. [7]

This paper aims to use a cost-effective tri-axial accelerometer to aid care personnel with their caregiving tasks and in turn, increase the well-being of the residents. Additionally, these accelerometers must be unobtrusive so that they do not cause any discomfort for patients. We discuss the approach of unobtrusive in/out of bed detection and in-bed movements to aid with the previously mentioned health issues. In the second section, we discuss the data collection procedure and various settings that were used. In the third section, we discuss the results of our accelerometer and CNN based approach for activity tracking in the bed. Conclusions are drawn and future directions are pointed in the last two sections, respectively.

2. Methodology

To validate whether the movements from patients can be tracked via an accelerometer on the mattress, we must sample/capture data from different test subjects and use Machine learning (ML) algorithms to detect the user actions. In this section, we first discuss the data capturing methodology and we furthermore discuss how data processing is done.

a) Activities must be detected

To cope with the previously mentioned health issues, we must check the feasibility to detect different kinds of actions.

These activities are as mentioned below.

- In/out of bed event detection: Detecting if a resident is in or out of bed could not only be used for night wandering but also for fall detection. It can also be used to determine the starting point for other activities like agitation and movements. To detect the in/out of bed detection we divide the in and out of bed action into different sub-actions. The in-bed detection will consist of the sit-down movement followed up by a lie-down movement. On the other hand, the out of bed detection will first have a sit-up action succeeded by the stand-up action.
- Agitation event detection: As there is a direct link between agitation and incontinence, detecting agitation might indicate that there is a need for an intervention.
- In-bed movement event detection: Tracking in bed movements, e.g. a movement from the back to the side position, could help with preventing pressure ulcers. Once the in-bed event has happened, an in-bed movement should be detected for patients with risk. If a resident at risk does not move within two hours, he must be moved manually to another position to relieve the pressure point and thus preventing pressure ulcers.

b) Data collection

To gather the accelerometer data, an Android app was made. This app requires the user to do a series of movements in the bed and samples the accelerometer data. The movements are as follows: 1. Do nothing 2. Sit down 3. Lie down on the back 4. Sit up 5. Stand up These actions are performed in a loop by a participant to sample data of these movement. This cycle is done a few times in a row per participant to get enough data. This cycle is shown in Figure 1. In a single movement, 200 accelerometer data points (x, y, z) are captured over 4 seconds. Via a beep in the smartphone application the participant knows when to do the next motion.

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Figure1. Matrix of confusion for one location's validation set

To capture data, some variability aspects must be considered. Firstly, we need to consider the sensor position relative to the resident. To see the influence of the position we take 10 cycles on 4 positions on the bed. After this, we randomly place the sensor in between the points and get 10 cycles again to validate if also this can be detected. Secondly, another consideration that we should make is that each bed is different. Thus, data needs to be captured on different beds. Twenty to thirty cycles of data are captured from different people, doing the actions on different bed settings, to see if the model can still classify the data. Thirdly, we investigated the effect of adding three new actions to the existing 5 actions described previously.

The three other movements are:

1. Roll from back to the side
2. Roll from side to back
3. Move arms and legs slightly (agitation).

c) Data processing

A convolutional neural network is used to classify the actions. We also investigate how the previously mentioned variabilities affect the machine learning model. With each variability a new model is created. The first step is to pre-process the data samples which are the 200 samples per single motion. In this pre-processing step we scale the data to the unit variance. This to make sure that they are in the same range and haven an equal dominance as feature inputs. The scaled data is then reshaped to fit as input for the CNN. As each sample includes the x, y and z axis of the accelerometer it will reshape it to a 3 by 200 array. The data is then split into training data, test data, and validation data. If an additional location or bed setting is tested, extra observations are used as validation data, else 80% training data, 10% test data, and 10% validation data is used.

As CNN we use a simple channel 1D convolutional network. The CNN model consists of two 1D convolutional filter layers with 64 filters, a dropout layer, a max-pooling layer, a flatten layer, and two dense layers of which the last one is the SoftMax function to provide the final classification of the movement.

3. RESULTS

After sampling the data from all the test subjects, we want to process this data to see the effectiveness of CNN models for the task at hand.

a) CNN for activity detection from a single individual using a single sensor

As an initial investigation, data from one person without any variability was used. This data was sampled with the same phone and each time on the same location. 10% of the data is used as test data and 10% as validation data, the rest of the data is used as training data. When training the model with the training and optimizing via the test data, the model provided an accuracy of 100% on the test data.

The validation dataset (10%) is used to verify if the trained model is correctly classifying the data. In Figure 2 we can see the confusion matrix of this validation set. This shows that the model also has a 100% accuracy upon the validation data.

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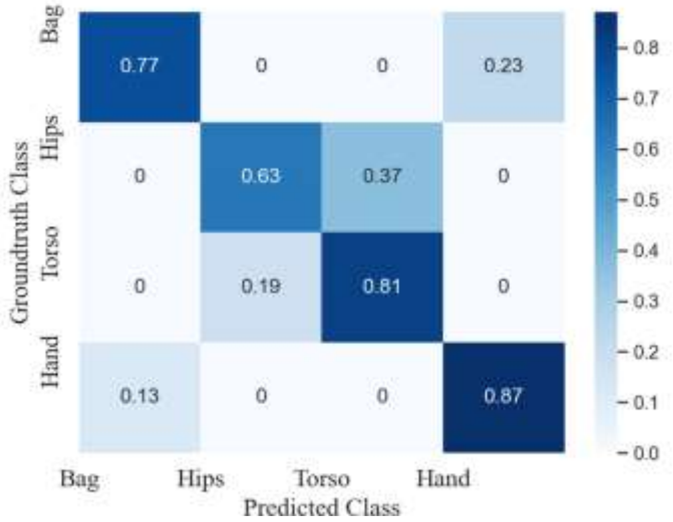

Figure 2. Confusion matrix of a location's validation set

b) Reproducibility between sensor positions on the same bed

As the location of the sensor might change on the same bed in a real nursing home, we train the model on four different sensor placements on the mattress. On each location, 10 cycles of data were sampled. After training on the accelerometer data from these locations, we reach an accuracy of 97.5%.

As a validation set, samples from a fifth independent location on the mattress is used. On this location also 10 cycles of data are sampled. The confusion matrix for the fifth location can be found. The used model was the trained model using the other four locations. It shows an accuracy of 92%. This shows that the model, trained on multiple locations of the bed, is still able to still classify data on other locations with slightly lower accuracy.

c) Reproducibility on different participants

Data from four participants, with each their bed setting, was sampled. Twenty cycles of each person were sampled and used as input for the model. An accuracy of 91.25% is reached on the test data. To check if the model is usable on a new bed, we train the model with data from three people with different bed settings and use 10 cycles of the fourth person as validation data. An accuracy of 93 % is reached when training with the data from three people. When validating this model with the data from the fourth, we reach an accuracy of 46%.

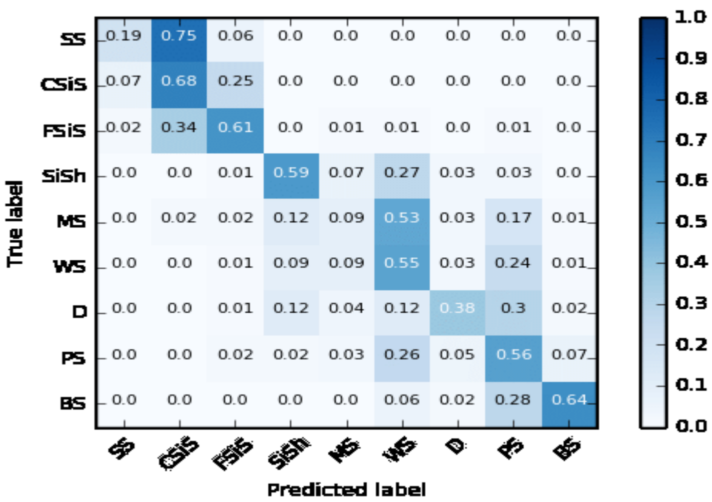

Figure 3. Confusion matrix of one bed used in a model trained on four beds

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As seen on the confusion matrix in Figure 3, only some of the actions are correctly classified. The model was trained by data from four independent individuals, not only the bed type and person will be variable but also the smartphone orientation and type of smartphone which might have different accelesensors will be variable.

If we repeat the experiment, but with seven different bed settings (all have been sampled for 20 to 30 cycles) instead of three, the model achieves an accuracy of 90.80%. When validating this model on an independent eighth bed (10 cycles) an 82% accuracy is achieved. These results indicate that if the model would be trained with a lot more data on different environments, the model might have an even better performance.

To be able to detect more health issues, there is a necessity to detect more actions. The three extra actions (see section II) were also performed for 30 cycles. Together with the data from the single location they were used to train a new model to detect more activities. This shows that it is also possible to detect other movements in the bed. The validation of this model was done with 10% of the data.

4. CONCLUSION

In this paper, we investigated if human activity tracking can be done by using unobtrusive sensors in the bed. This to aid nursing home residents with their care needs and nursing staff with their care tasks. We have shown that it is possible to classify human actions in a bed by using a 1D convolutional network. On a single location in a single bed, an accuracy of 100% is reached. When adding more movements to the system it has a slightly lower accuracy of 96%. If more locations are considered on a single bed, we reach an accuracy of 92%. This shows that human activity tracking is possible even with variable environments if there is enough data.

5. FUTURE WORK

Data collected from more subjects may aid in designing a robust activity classification system. To increase the accuracy of the system even further, hyper parameter optimization can be done on the different layers of the CNN model. Also the influence of sensor orientation on the accuracy has to be checked. To validate if motions can be tracked from the elderly, measurements must be done on real subjects in nursing homes to get accurate data. These can be converted to recommendations for the nursing staff. A specifically designed embedded system can be made to capture accelerometer data, running inference model of this so developed CNN on that in real-time will be the ultimate goal.

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