RECOGNITION OF ARM POSITIONS OF DEMENTIA PATIENTS VIA SMARTWATCHES USING SUPERVISED LEARNING

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ABSTRACT
Currently, about 46.8 million people worldwide have dementia. More than 7.7 million new cases occur every year. Causes and triggers of the disease are currently unknown, and a cure is not available. This makes dementia, along with cancer, one of the most dangerous diseases in the world. In the field of dementia care, this work attempts to use machine learning to classify the activities of individuals with dementia in order to track and analyze disease progression and detect disease-related changes as early as possible. In collaboration with two care communities, exercise data is measured using the Apple Watch Series 6. Consultation with several care teams that work with dementia patients on a daily basis revealed that many dementia patients wear watches. In this project data from the aforementioned sensors is sent to the database at 20 data packets per second via a socket. DecisionTreeClassifier, KNeighborsClassifier, Logistic Regression, Fast Forest, Support Vector Machine, and Multilayer Perceptron classification algorithms are used to gain knowledge about locating, providing, and documenting motor skills during the course of dementia. As a first step, arm position sequences are to be identified, from which different fine-granular activities are to be classified later.

KEYWORDS
Human Motion Analysis, Machine Learning, Dementia

1. INTRODUCTION
As a result of demographic changes, there are far more new cases of illness than deaths among those already ill. If there is no breakthrough in prevention and therapy, the number of dementia patients will increase to 74.7 million by 2030 and to around 131.5 million by 2050 according to population projections. In Germany alone, this corresponds to an average increase of around 40,000 dementia patients per year or around more than 100 per day, according to the German Federal Ministry for Health (Bundesministerium für Gesundheit 2020).

The shortage of junior staff due to the lower birth rate is leading to a decrease in population figures and a massive increase in people in need of care. This work deals with the machine tracking of activities during the course of dementia by means of sensor technology. Main part of this work is a system that is able to collect data from smartwatches in real time and send it to a server for further processing via a Web-Socket.

In cooperation with several nursing communities, with this work the measurement of training data using Smartwatch starts. A consultation with various nursing teams that work with people suffering from dementia on a daily basis has shown that many patients wear watches. Smartwatches allow for an unobtrusive way of measuring data. These devices usually integrate the following: global positioning system (GPS), accelerometer, light sensor, gyroscope, magnetometer, ambient temperature sensor, heart rate monitor, oxymetry sensor, skin conductance sensor, and skin temperature sensor.

This work answers the following question: Which Apple Watch sensor technology and which machine classification algorithms can be used to detect arm positions in dementia treatment?
2. RELATED WORK

Health information technologies have been revolutionizing healthcare for years. The variety and range of software and hardware technologies as well as the number of applications has increased considerably. There is an increasing global demand for the implementation of health information technologies in hospitals, clinics, and homes according to Lau et al. (Lau et al. 2019). In their work, they investigate the current status of mobile devices and software in relation to health information. In contrast to traditional health interventions originating from clinical researchers, mobile health applications are often developed commercially with little input from clinical researchers or consumers. Portable devices such as smartwatches and fitness tapes are becoming increasingly popular in all demographic groups, from children to older adults. Reasons for this increase are fitness tracking and health monitoring. According to Malu and Findlater, detecting mental and physical disorders and supporting people with difficulties can significantly improve the health of users (Malu and Findlater 2016). Several of these applications are based on data collected by sensors on smartwatches, including heart rate monitor, GPS, accelerometer, and gyroscope. Various interaction techniques make smartwatches unique and ubiquitous as a data tracking device. The literature supports this statement in various works of the past years.

Ravi et al. (Ravi et al. 2007) have successfully measured various human activities using an accelerometer. Shoaib et al. (Shoaib et al 2015) have used both smartphones and smartwatches together to identify various daily human activities.

Dong et al. (Dong et al. 2013) as well as Ramos-Garcia and Hoover (Ramos-Garcia and Hoover 2013) have measured eating cycles of smartphones users. In these studies, accelerometers and gyroscope sensor data from smartphones were used. Da Silva and Galeazzo (Da Silva and Galeazzo 2013) obtained various data on eight daily actions using accelerometer data, using an EZ-430 Chronos smartwatch. It should be noted that the detection of general activities is possible using accelerometers and gyroscope sensors. However, it is necessary to realize these activities for the health-related data in a much more fine-grained way. A crucial point is the arm movement detection. In their project in which only inertial sensors of the smartwatch were used, Jose Manjarres et al. (Jose Manjarres et al. 2019) present the challenge of recognizing human behavior by means of arm motion detection and its possibilities. They were able to calculate the workload according to the Frimat method using trained random forest with an accuracy of 97.5% in validation and 92% accuracy in real-time tests with 20 subjects.

Xu et al. (Xu et al. 2015) classified hand and finger gestures as well as characters from smartwatch motion sensor data. Similarly, Riaz et al. (Riaz et al. 2015) and Tautges et al. (Tautges et al. 2011) attempted to reconstruct body movements using several portable devices by comparing accelerometry data with the data generated from motion detection.

The present work is most similar to the project of Serkan Balli et al. (Serkan Balli et al. 2018). In their work, using an accelerometer and gyroscope in a smartwatch, the authors extracted 14 features from the obtained sensor data, condensed them through a dimensionality reduction algorithm filter and tested several methods (C4.5, SVM, random forest and kNN methods) for classifying human actions on five subjects to identify the following activities: brushing teeth, walking, writing on paper, writing with the keyboard, and vacuuming. The study shows how well machine activity classifications can be realized using the sensor technology of smartwatches. For example, writing using the kNN method was rated with a success rate of over 98%. Random forest and C4.5 methods classify the action walking with 100% accuracy. The present project extends the applied motion sensors (accelerometer and gyroscope) by the pedometer and heart rate sensors. The authors expect that this will represent an improvement beyond the state of the art.

This work demonstrates the potential that smartwatches offer for the healthcare sector. In the following, the prototype is described.

3. CONSTRUCTION – MACHINE LEARNING

For this work, a standalone watchOS application for the Apple Watch Series 6 was implemented using state-of-the-art technology. The application communicates with a WebSocket that both outputs the watch data packets to a user interface and stores them in a MySQL database. The backup of the data is used for further machine processing.
The application provides methods for querying motion and health data, temporarily saving data in the smartwatch memory, labeling data, and an interface for exchanging sensor data with a web server via WebSocket. In case of complications, backup methods can trigger a resend of sensor data generated in a session. Instead of caching sensor data in a CSV file on an iPhone, this work enables direct reuse of sensor data on the server side in real time.

The sensor technology in the focus of this work controls through the application in detail accelerometer, gyroscope, gravity, and heart rate sensor as well as the electrical heart sensor (ECG). Figure 1 provides an overview of the work. Accelerometer, gyroscope, and magnetometer contribute to the mathematical calculation of the device orientation. The gravitational acceleration can be used to determine where south is, and the magnetic field vectors can be used to determine where north is from the device’s point of view.

![Figure 1. Overview](image)

Rotation values of the gyroscope are integrated to estimate the deviation from the previous position. Thus, the combination of several sensors is used to calculate the attitude and to use the strengths of each sensor to compensate or minimize the weaknesses of each sensor. Since an acceleration sensor picks up any forces such as vibrations, this can cause unwanted noise. All movement and health data tracked by the realized application is first stored as arrays in a respective predefined structure and then encoded as JSON and then prepared for data exchange.

The data per second does not represent a temporal progression, but only a snapshot of the sensors. The data we tracked is at the temporal frequency of 20 hertz (Hz). Each of the data packets tracked at intervals of 50 milliseconds contains the following parameters: accelUserX, accelUserY, accelUserZ, attitudePitch, attitudeRoll, attitudeYaw, gravityX, gravityY, gravityZ, gyroX, gyroY, gyroZ, and heartrate.

When creating the test and training data, it was agreed that the movement would be approximately six seconds long. With one data record every 50 milliseconds, this corresponds to 20 data records per second and thus 200 data records in total (20 data records/second * 10 seconds). It has been found that the prediction accuracy improves significantly if instead of averaging 200 data per label at 20 Hz for the 12 features (4 sensors * x, y, z), the amount of data per half second is averaged and a new feature is formed from each averaging. This results in 240 features with 20 data sets per second and 12 original features. The data was divided into blocks of 0.5 seconds, with the mean value over the values being calculated for each block. Thus, twelve values must be determined for each feature (20 * 0.5 seconds = 10 seconds). In the example of 200 lines (= 10 seconds), the average of a block is thus formed over 10 lines. With a label duration of 220 lines (= 11 seconds), this results in 12 lines (rounded down to 20). In order to include these in the calculation of the average, they are distributed to the individual data sets (in this case to the first eight data sets). This ensures that there are always exactly twelve features for a value (e.g., AttitudePitch1, AttitudePitch2, ..., AttitudePitch20). The actual duration of the labels is thus variable, while the number of features remains constant. In summary, the length of the label determines the number of features, and the amount of data per feature is determined by the frequency (Hz) of the sensor.

4. RESULTS

The previously described methodology was applied to different classification algorithms in a series of experiments. Five subjects were included, generating 60 labels per arm position sequence. Figure 2 shows the different arm position sequences of the subjects.
Each sequence (A to D) consists of two arm positions, each held for 3 seconds. The measurement rate of 20 Hz results in $4 \times 5 \times 60 \times 20 = 24,000$ data sets per test series. The subjects wore the watch on their dominant hand at all times. The test and training data were created separately, i.e. the data of one subject were compared with the data of the other four subject. The test series shows how the best classification algorithms perform with different sensors (cf. Table 1).

Table 1. Predictive power of two classification algorithms with different sensors

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Sensors / Prediction</th>
<th>Sensors / Prediction</th>
<th>Sensors / Prediction</th>
<th>Sensors / Prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logistic R.</td>
<td>Acceleration 65.56%</td>
<td>Attitude 96.67%</td>
<td>Gyro 85.24%</td>
<td>Gravity 99.44%</td>
</tr>
<tr>
<td></td>
<td>Acceleration, Attitude 96.94%</td>
<td>Gyro, Acceleration 89.44%</td>
<td>Gyro, Attitude 96.94%</td>
<td>Gravity, Acceleration 100%</td>
</tr>
<tr>
<td>Fast Forest</td>
<td>Acceleration 97.5%</td>
<td>Attitude 96.67%</td>
<td>Gyro 98.33%</td>
<td>Gravity 100%</td>
</tr>
<tr>
<td></td>
<td>Acceleration, Attitude 99.72%</td>
<td>Gyro, Acceleration 98.33%</td>
<td>Gyro, Attitude 99.44%</td>
<td>Gravity, Acceleration 99.72%</td>
</tr>
</tbody>
</table>

An important finding are the clear results of the Gravity Sensor alone and in combination with any other sensor. It seems that by changing the gravity, the hand position can be clearly defined.

The good results of the hand rotation detections represent another important finding. We initially assumed that heart rate and arm movements would provide clear data on respective activities; however, this assumption was wrong. Over 80% of the performance are a result of hand movement and rotation detection. A visual comparison also confirms the high performance of the hand motion sensor technology. Figure 3 shows the direct comparison of the data between the acceleration sensor on the right and the gravity sensor on the left.

Figure 3. Comparison Acceleration Sensor (right) and Gravity Sensor (left) – A: Turquoise, B: Orange, C: Blue, D: Red

The differences in the movements are clearly visible with the Gravity Sensor, which also makes it easier for the classifier to classify them. This is a crucial piece of knowledge, hence the sensor technology must be given much more weight. It is the decisive factor that enables the recognition of very similar movements.
5. CONCLUSION

Based on our research, the interaction of the accelerometer, attitude sensor, gyroscope and G-sensor in combination with Logistic Regression and Fast Forest algorithms turns out to be the strongest combination for classifying arm position sequences. It should be noted that as a sole sensor, the G-sensor axes (Gravity - X, Y and Z) perform best. The magnetometer worsens the classification, and the heart rate plays a minor role in arm position sequences so far.

This work answers the question about the classifier and the required sensor technology for the detection of arm positions using smartwatches:

- **Logistic R**: G-sensor and Acceleration, G-sensor and Gyroscope
- **Fast Forest**: G-sensor, G-sensor and Attitude, G-sensor and Gyroscope

In the next step, based on this work, we will test the classification reliability of the favored algorithms with the four sensor systems on different frequency and on different activities, which in turn can only be recognized via the hand position. As one possibility, we will now try to classify very similar activities. For example, with the state of the art, movements such as drinking (bringing a glass to the mouth), eating (bringing a fork or spoon to the mouth) cannot be distinguished, since the sensory system hardly shows any differences due to the almost identical movement. It is these movements that we can now attempt to investigate using our work and the classifiers and sensors previously evaluated.

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