Recognizing Drinking ADLs in Real Time using Smartwatches and Data Mining

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Abstract

Automatic detection of ADLs – activities of daily living – is one focus of research in ambient assisted living, esp. for elderly people. Allowing the elderly living as long as possible at home is one of the big challenges today of our ageing society. We have developed a smartwatch based application which automatically detects drinking ADLs. After having gathered sensor data from smartwatches from about 1300 different ADLs we used data mining to develop various drinking recognition models (neural nets, logistic regression…). We could demonstrate that these models predict drinking ADLs at a very high rate and that the models discriminate them from other ADLs. In a next step we implemented the model in a smartwatch. The app detects drinking ADLs now in real time. The concept has been proven to be very successful and it is planned to incorporate this model in a smartwatch based emergency call app and to extend the approach to other ADLs.

Keywords: smartwatches, dehydration prevention, ADL, MCI, drinking detection, data mining, sensors, apps, Android, Tizen, emergency support, elderly people, AAL, ambient assisted living

1 Smartwatches as new gadgets

Smartwatches (see figure 1) are one of the mega trends of the next years ([21]), Gardner's hype cycle puts it around the peak of inflated expectations ([10]). Several companies like Samsung, Sony, LG, and Motorola are now offering various smartwatches based on Android Wear, Samsung also promoting its own Tizen OS with the Samsung Gear S. The smartwatch market will gain even more momentum with the Apple watch ([3]) based on Apples iOS. Looking at the pre-orders and actual sales for the Apple Watch – several millions - one immediately recognizes the potential of this new type of personal device.

Figure 1: Smartwatch Samsung Gear S running a specialized emergency app, supporting elderly or handicapped persons, e.g. with MCI (mild cognitive impairment) (see [14]).

Based on a search for smartwatch apps that are already available or being released shortly the following main target groups can be identified as:

a) Sportive people using the smartwatch for collecting different types of sports activities, actually the area of self-quantification (see [15], [1] or [20])
b) Using it to provide some notifications, e.g. short text pieces or SMS texts.
c) Indicating phone calls, although most smartwatches - with the exception of the Gear S - require a mobile phone connected via Bluetooth for taking phone calls and cannot act standalone. Apple and now also Android Wear support phone calls through WLAN if the mobile phone is located in the same WLAN as the smart watch.

In the first area the data are collected and graphically visualized in so-called eHealth or self-quantification portals and providing the operators of the portals with “free physiological and medical data in the terra byte area” (e.g. [22], [9],). A good example is the partnership between Apple and IBM which shows the high interest of big companies in this multi-billion market ([6], [11]) and how they intend to use it for data mining, e.g. for medical research purposes.

Interestingly enough the market for apps which can or will support elderly people with some kind of impairments requiring a non-discriminating device seems to be totally ignored. No apps have been published so far which are targeted towards the specific needs of this user group. The target group is even bigger if one takes the needs and requirements of their relatives who may care for them at home into account. Today's society and politics encourage elderly people to live at their home as long as possible. Eldercare in specialized institutions is quite expensive, for major populations not really affordable. In addition most elderly prefer to stay in an environment they know, have friends, relatives etc. around.

Several "gadgets" try to support this user group, as an example special wrist bands, mobile phones for the elderly with bigger keys, specialized high contrastive displays etc. The disadvantage of those tools is the stigmatization effect associated with those devices. Wearers can be immediately recognized by others as having some kind of handicap. This holds back potential wearers using these obviously useful tools. Smartwatches overcome this as they will be worn by many people across all ages and thus prevents wearers to be recognized as handicapped.

2 The problem: insufficient fluid in-take of elderly people

One of the most severe health problems of elderly is ongoing dehydration. Insufficient fluid in-take is mainly caused by the diminishing sensation of thirst at higher age drinking ([5]). The hypernatremia caused by the dehydration evokes subtle lethargy, weakness, irritability, phantasmagorias and lack of concentration enhancing domestic accidents, tumbles. Invasive systems which measure some vital parameters from blood etc. are difficult to handle and will not be accepted by the majority of users. The easy and non-obstructive monitoring of sufficient drinking in order to avoid dehydration is one of the rationales and aims of our work.

In general activities like drinking are called ADLs: activities of daily living (see [25]). Typical ADLs are: drinking, eating, walking, tooth cleaning, sleeping, reading newspapers, watching TV, making telephone calls, searching the internet and so on. Changes in the sequence or frequency of ADLs can give first hints if the state of health of a person has changed or is changing ([8]). A typical example of such an indicator is the amount of fluid elderly drink per day, if a person does not eat at regular times or if getting up in the morning changes drastically.

3 The solution: Supporting elderly people with smartwatches

Smartwatches represent an ideal tool for discovering ADLs, esp. drinking acts. Based on sensor measurements an app can detect drinking ADLs in real time and alerts its wearer if no or not enough drinking ADLs are recognized within a certain time span. In addition various statistics can be computed over a longer time period, e.g. as an information source for physicians. Furthermore smartwatches can provide the user with a lot of different additional information (time, phone calls, reminders …), esp. for people with MCI (mild cognitive impairment, see [19]).

We have developed several apps for Android and Tizen based smartwatches which supply their wearers with specific support functions, e.g. some reminder functions, emergency call functionality, warning when leaving special areas etc. (see [14] and figure 1). One of the intended target functions of the app is to detect potential dangerous medical situations and helping the wearer to avoid or encounter these situations, e.g. by detecting tumbles, long inactivity periods… In more general terms we want to detect all kinds of ADLs. Once we detect specific patterns and changes in these patterns we will be able to inform the user, his or her relatives and doctors with these detected changes and allow them to start specific actions.

A key function of the app is to remind its wearer that it is time to drink. This is done by counting the number of drinking ADLs within a specific time period (see [4]).

For further discussions on general sensor support in AAL (ambient assisted living) see [12] or using video detection based approaches see [7]. For further attempts detecting daily activities with different sensors and cameras see [23], [16], [17], [18] and [24].

4 Section

Smartwatches and wearables are equipped with many different sensors like gyrometer, accelerometer, GPS, magnetometer or barometer (see figure 2). Those sensors form the basis for many applications, e.g. counting steps, wrist-up detection, inactivity periods, sleeping quality and for our drinking detection app.

Figure 2: Running a sensor service on an Android Wear based smartwatch, gathering data from all available sensors. Data are gathered in background.

Detecting drinking activities is not a trivial task as we need precise methods to distinguish the drinking ADL from similar ADLs like eating, standing up etc. Figure 3a-c gives an example of the sensor data produced during a breakfast situation consisting of different ADLs like drinking, eating, newspaper reading etc. The only data available for the activity detection are the sensor data delivered by the smartwatch, no visual input is available or used. As the time resolution of the sensors also differs quite heavily from hundreds of measures to one measure per second additional pre computations have to standardize all measures into an appropriate equally spaced time grid.

One – obviously towards physics oriented - solution could be to model the drinking activity based on the movements involved when raising a cup or glass, moving it forward up to the mouth, tilting it short before it reaches the mouth, stopping, moving backward and so on. The movement is split up in several space vectors and related to acceleration, rotation etc. Although this approach can model an ideal drinking ADL it may be difficult to apply it to different persons and different situations.

We have chosen another approach, a data driven modelling process. We first collect the sensor data from many drinking activities and other activities and then apply a data mining process to these data. From that we develop some characteristic functions and use them to detect the activities in real time.

We divided the whole process into a four step procedure (figure 4) which realizes the drinking activity model. In a further step we use this to implement this functionality in a smartwatch for real time drinking detection.

5 The data collection process

In a first step we developed a sensor data collection app (figure 5). With this app we collected about 1300 different activities starting from drinking, walking, eating etc. from different persons using different smartwatches (Sony Smartwatch 3, Samsung Gear Live and S). The app reads the sensor data for about 10 seconds and stores them into a csv file. The time period of 10 seconds was chosen to ensure that the drinking act was really finished and to make it easier to differentiate it from other ADLs. Further versions may be based on a shorter time period. These collections are used as the training data set.

Figure 6a-c shows a graphical example of such a training activity for three sensors and the rotation of the arm. In this case all the data have been standardized with regard to equally spanned time periods. The sensor values have been interpolated into 20 millisecond intervals with overall 500 interpolated values. Visual comparison with other sensor data collected from different people show a high similarity between the graphs. Based on that we were convinced that data mining could provide us with a reliable model.

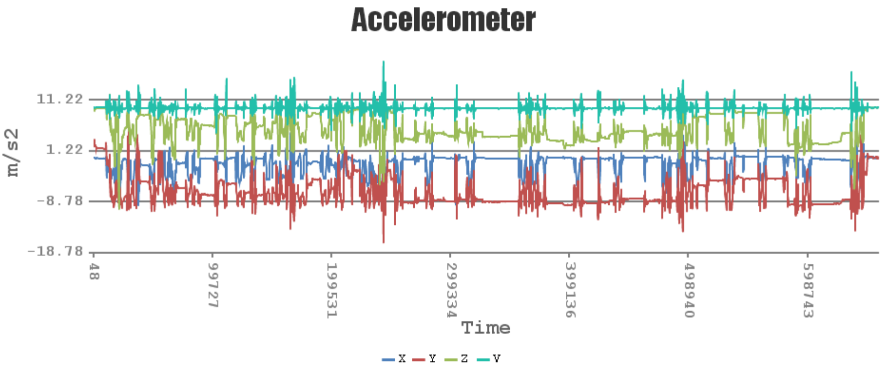


Figure 3a: Typical example of several sensor measurements during a breakfast with a smartwatch. Overall 3300 acceleration and gyrometer measurements and 6600 magnetometer measurements for a time period of about 11 minutes were gathered. Figure 3a shows the accelerometer values for the x, y and z axis. In addition the combined acceleration from all three axis (based on euclidian distance) was computed.

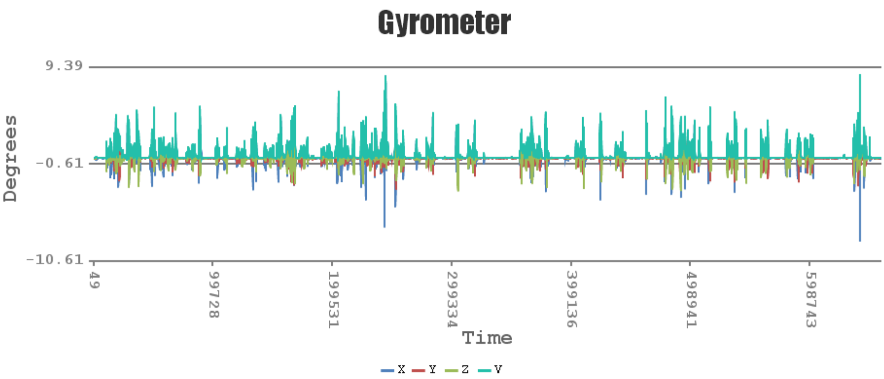


Figure 3b: The gyrometer value in degrees for the ADL above. Please note that the sensors run with different temporal resolution.

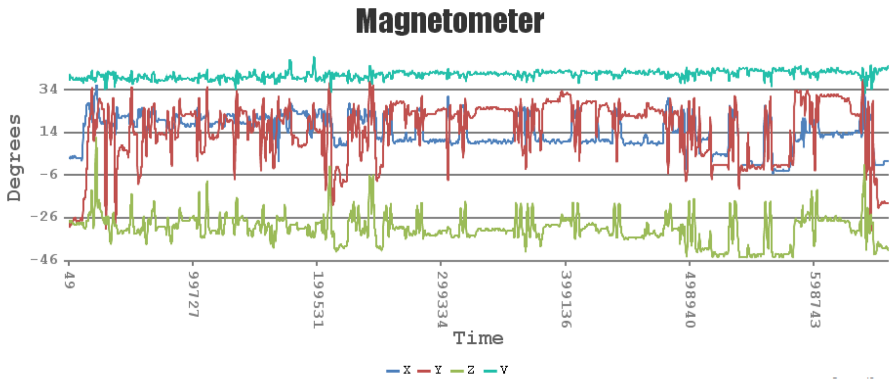


Figure 3c: The magnetometer values for ADL above.

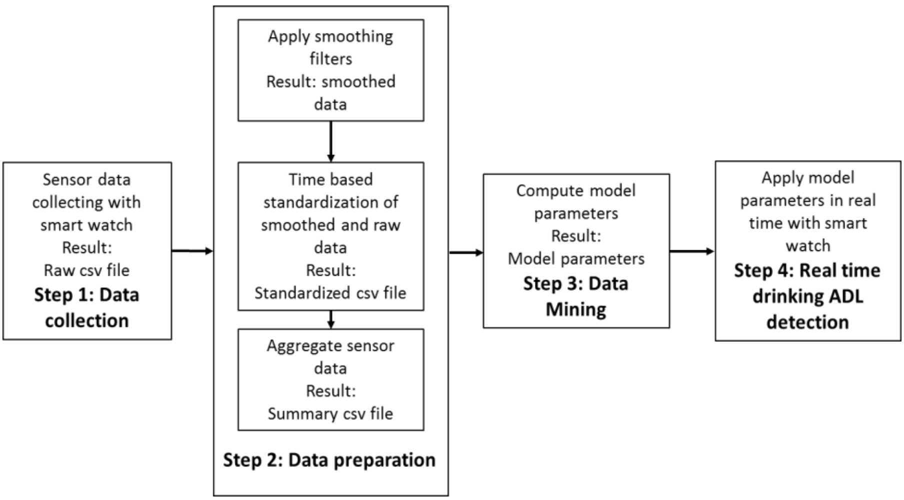


Figure 4: Four step process – from sensor data collection to real time drinking activity detection

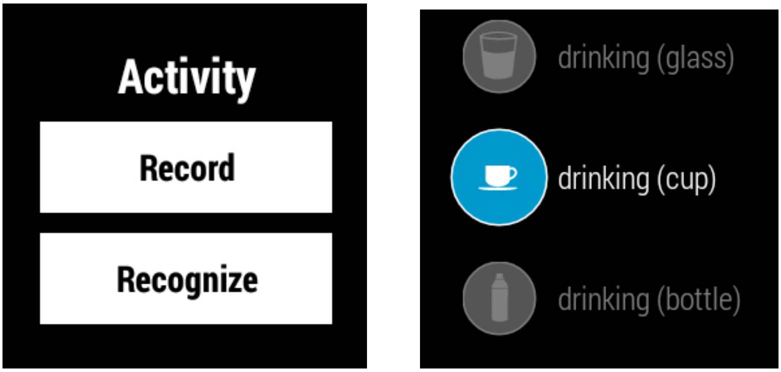


Figure 5: Android Wear app for collecting sensor data and defining current activity; left side: recording data, right side: tagging of currently measured ADL for various drinking situation using a glas, a cup or a bottle (see [4]).

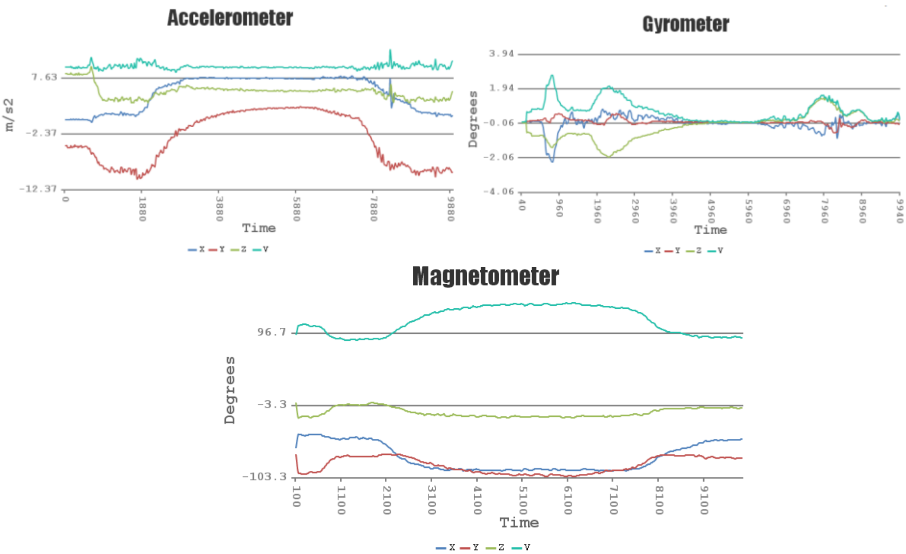


Figure 6a-c: Typical measurements of a 10 second training period for accelerometer, gyrometer, and magnetometer values.

Table 1 shows some raw data. Data are stored in a csv file for further processing.

```
-5;-1;1420537162191;WEAR;SmartWatch 3
-5;-2;1420537162191;TEXT;Trinken
0;1;1420537162281;WA;0.22500217;-4.495256;8.478273
0;2;1420537162288;WA;0.22500217;-4.437809;8.305931
0;3;1420537162304;WA;0.12925656;-4.8973875;8.305931
0;4;1420537162314;WG;-0.005326745;0.0;-0.018643608
0;5;1420537162318;WA;0.30159867;-4.5144053;8.612317
…
0;16;1420537162368;WG;-0.039950587;0.0026633726;-0.029297099
0;17;1420537162369;WA;0.32074776;-4.5527034;8.439975
0;18;1420537162374;WG;0.031960472;0.069247685;-0.5619716
0;19;1420537162387;WA;0.22500217;-4.5718527;8.056993
0;21;1420537162387;WG;0.045277335;0.07191106;-0.5619716
0;22;1420537162398;WG;0.058594197;0.07191106;-0.56729835
```

Table 1: Example raw data retrieved from the smartwatch.
For more details see [26]

The csv file contains the measurement time (in milliseconds), the sensor (WA = accelerometer, WG = gyrometer, WM = magnetometer; rotation not shown here as not used in the analysis) and the value of the measures from the sensor. The first two lines store the type of watch used (Smartwatch 3) and the second line the activity (TRINKEN = drinking).

6 The modelling process

In the second step the collected sensor data are normalized. Steps 7.1 and steps 7.2 were run using small R-scripts outside RapidMiner. The reason was that we wanted to keep those steps as environment neutral as possible as we had to port those steps for the real time detection process on the smartwatch with its programming language restrictions (Java, JavaScript) and limited processing power.

6.1 Smoothing and standardizing data

All sensor data are first smoothed by applying filters (e.g. hi/low pass) and standardized with regard to measuring time. Table 2 shows an example of the time standardized data derived from the raw data. The example uses 20 millisecond intervals.

```
s_A;time_A;x_A;y_A;z_A;s_G;time_G;x_G;y_G;z_G;s_M;time_M;x_
M;y_M;z_M;s_R;time_R;x_R;y_R;z_R
A;40;0.28950448578947;-
4.5174288736842;8.5609167368421;G;40;-
0.0084340129166667;0.0015536340166667;-
0.020197241666667;M;40;;;;R;40;;;
A;60;0.21064033;-4.6484492;8.2963565;G;60;-
0.033292156;0.005326745;-0.0292970985;M;60;;;;R;60;-
0.109693386;0.6582455;-0.72389895
A;80;0.244151285;-4.7729182;8.3825275;G;80;-
0.043679308733333;0.00390627972;-
0.0305400064;M;80;;;;R;80;-0.109693386;0.6582455;-
0.72389895
A;100;0.25691736666667;-
4.5654696;8.1846536666667;G;100;0.039131090538462;0.0706818
1;-0.5619716;M;100;-62.011962686567;-
70.799604477612;0.86492537313433;R;100;-
0.12131360294737;0.57195355263158;-0.79768584157895
```

Table 2: Example time standardized data retrieved from the smartwatch.

Each line contains now estimated sensor values (*A, *G, *M, *R) on a 20 millisecond time frame.

6.2 Computing characteristic attributes

Several statistical attributes (39 basic attributes like means, standard deviations, max, min, inter quartiles …) and FFT analysis (resulting in about 157 attributes) are computed for each collected activity. The attributes are structured in the following way: sensor type (ACC … accelerometer, MAG … magnetometer, GYR … gyrometer), statistical measure (MEAN, SD … standard deviation, IQ … inter quartile distance, FFT … FFT components etc.) and three axis (X, Y, Z). Each activity spans about 10 seconds as explained above. This results in an aggregated entry per activity. For each activity a data record was written into a summary file together with the information which type of activity was performed (Table 3). The summary file contains about 1300 entries.

DRINKBINOMIAL	ACC.IQR_Y	MAG.IQR_Y	ACC.SD_Y	MAG.SD_Y	ACC.FFT.Y1	ACC.FFT.X1	...	ACC.FFT.X9	ACC.FFT.Y6
true	2.0994	1.5363	1.2400	1.0655	-0.9445	-1.0141		-0.4631	-0.9172
true	2.1193	2.3964	1.8756	1.9786	-0.9956	-1.0771		-0.4101	-0.7378
true	1.2783	1.7784	0.8747	1.2040	-0.8423	-1.0771		-0.5690	-0.5585
true	2.3568	1.4780	1.7417	1.5552	-0.9956	-1.0141		-0.6749	-0.8275
true	3.0261	2.8665	2.6088	2.5032	-0.8934	-0.7622		-0.5690	-0.2895
false	-0.1873	-0.5898	0.1821	-0.8790	2.1726	-0.1955		0.0665	-0.4689
false	-0.5784	0.0607	-0.5854	-0.1924	-0.1269	-0.1325		-0.3042	2.9831
false	0.0394	0.2638	0.0024	-0.0594	-0.1269	1.1270		0.6490	0.3829
false	-0.1460	-0.0487	0.2727	-0.1846	-0.1780	-0.0695		-0.3572	0.8760
false	1.1509	0.8260	0.7655	0.3184	0.0775	-0.0695		-0.0924	1.2347
false	1.3691	1.4679	0.9200	0.9849	0.4352	-0.8252		-0.1983	-0.9620

Table 3: Example summary sensor data for various activities. One line represents one activity. True indicates a drinking ADL, false any other ADL.

6.3 Applying data mining

In a third step we applied several data mining techniques using RapidMiner (Figure 7) using the aforementioned normalized sensor data:

- logistic regression,
- clustering and
- a neural network
- random tree
- discriminant analysis

We used several different combinations of the variables from the summary file. We found that there is no real difference in the detection quality if we take all attributes (157 including the FFT analysis) or only the basic 39 attributes. Cross validation showed that drinking acts can be detected with a very high degree of accuracy (92% and 97%) depending on the model applied (see table 4).

We also computed the ROC for four methods (Figure 8): neural nets, logistic regression, SVM, discriminant analysis and as a matter of interest a random tree. As the resulting ROC shows the first four methods nearly do not differ in their performance, while random tree behaves worse.

This is high detection rate show that is possible to detect drinking ADLs just based on sensor data delivered from a smartwatch.

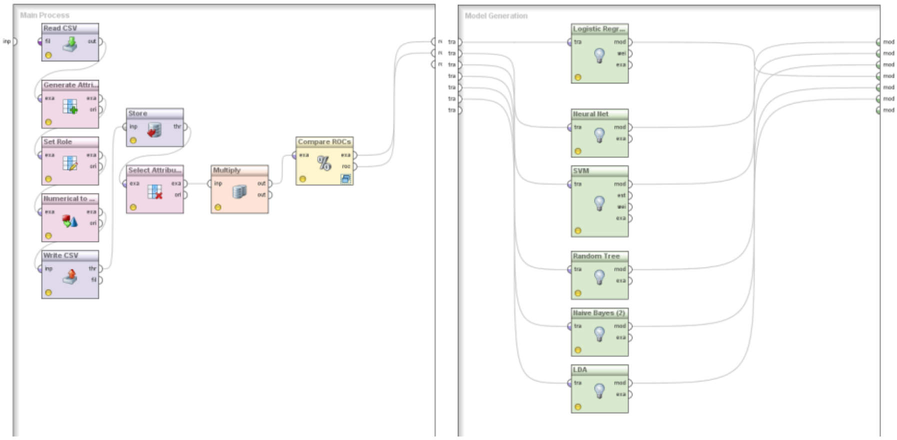


Figure 7: Example RapidMiner process

LogReg - time only	true false	true true	class precision
pred. false	**279**	**6**	97.89%
pred. true	5	**72**	93.51%
class recall	98.24%	92.31%	**362**

Neuralnet - time only	true false	true true	class precision
pred. false	**277**	4	98.58%
pred. true	7	**74**	91.36%
class recall	97.54%	94.87%	**362**

Table 4: Classification percentages with the logistic regression and neural net model (RapidMiner output) for 362 test cases (about 1000 examples used for training)

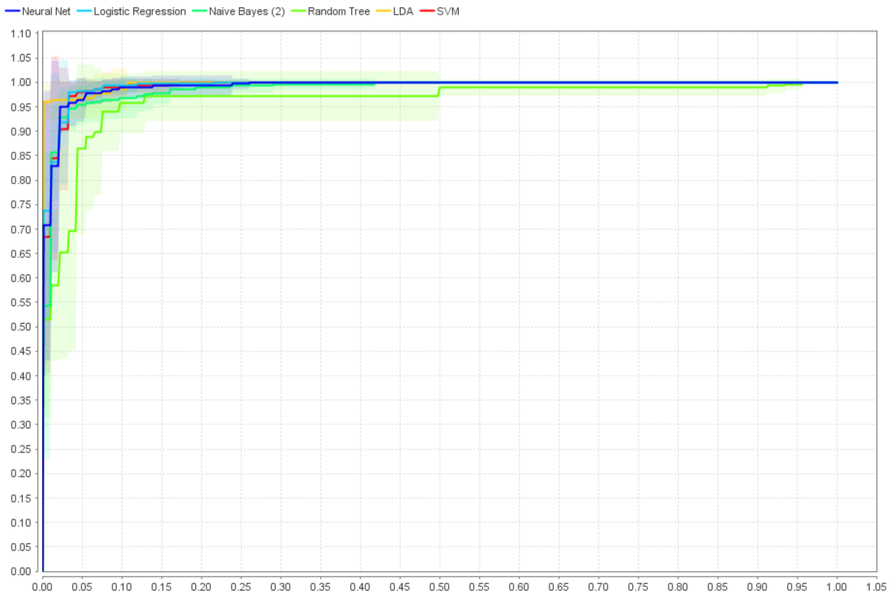


Figure 8: ROC using neural nets (dark blue), logistic regression (light blue), SVM (red), a random tree (green) and discriminant analysis (yellow)

7 Real time ADL detection

In a fourth step the regression weights from the logistic regression (created in the third step) were used to implement an experimental Android and Tizen (Samsung Gear S) based smartwatch apps. We decided to use the results of the logistic regression algorithm as the computational power of smartwatches is limited and we did not want to interfere too heavily with other parallel running processes. This is also the reason why we used just the basic attributes and did not use FFT attributes as the validation results have shown that FFT only has low impact on the recognition results. Languages used are Java and JavaScript.

A simple app (figure 10) was developed to test if the logistic regression parameters derived from the model discriminates drinking from other activities in real time ([4]). This is done using a five second sliding windowing approach (see Fig. 9; [13]). The app continuously reads the sensor data and stores the data for five second periods. Two five second periods are combined into a ten second period and the logistic regression is applied to this period. This should ensure that an ADL is detected independently from its start and end time.

Figure 10 shows that three drinking and 16 other activities have been detected. The model was tested with several users who did not participate in the training collection process. First experiments detect drinking ADLS quite precisely based on this procedure. The overall detection rate 87.6% is smaller compared to RapidMiner validation (see figure 11). This is mainly due to the false / positive rate. One reason for this might be that we need to make some optimizations for the filters within the smartwatch version. Differences in the detection rates also occur between different smart watches, mainly caused because of different sampling rates. This is clearly an area for improvement and further tests.

In another prototype the user is warned if the number of drinking activities falls below a certain threshold resp. an overall information notification is shown (see figure 12a and 12b). The emergency app issues a first warning if the threshold time was met. If the user does not react by quitting the notification and an addition grace period is gone the app calls a relative or an emergency support institution. Obviously this can be configured in the app. This concept has to be seen in connection with other support functions of the app, e.g. detecting tumble acts, leaving a defined area – so called geofencing (see figure 12c) and similar events.

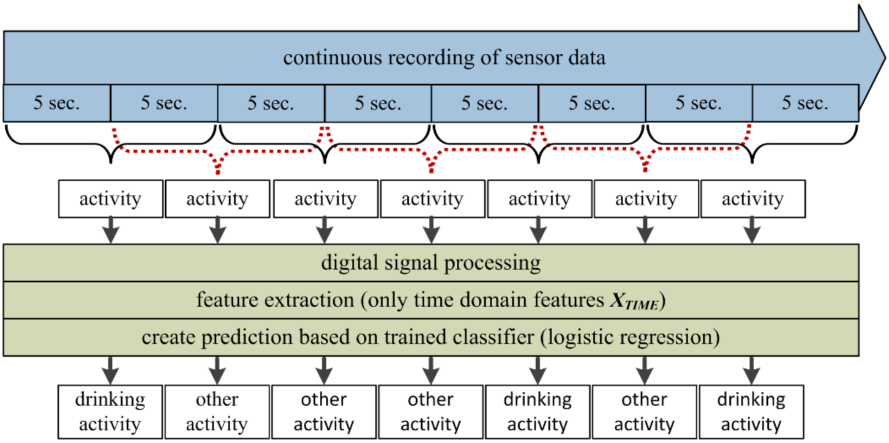
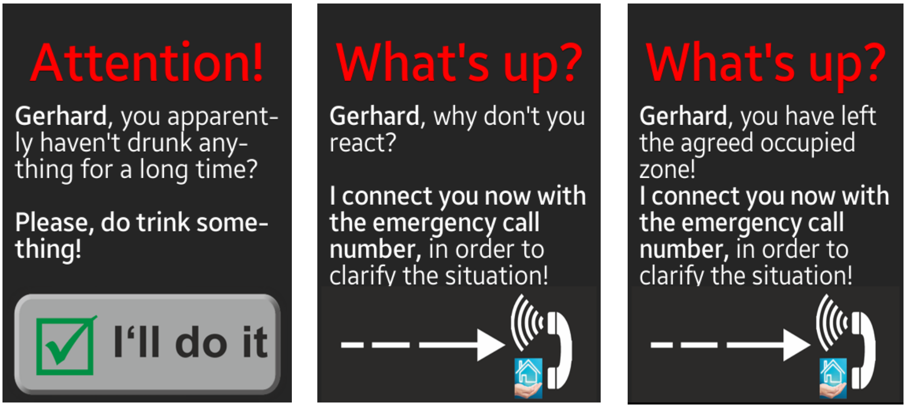


Figure 9: Real time drinking ADL detection process ([4], p. 62).

Figure 10: Test app using the logistic regression parameters detecting drinking ADL in real time

		Executed ADL	
		Drinking ADL	Non-drinking AD
Classified ADLS	Drinking ADL	30 (96.7 %)	12 (16.2 %)
	Non-drinking ADL	1	62 (83.8 %)

Figure 11: Example classifications with the real time app.



(a) Pre Alert (b) Alert call (c) Geo fence alert

Figure 12: Emergency call app warning the user that for a longer time periods no drinking ADLs have been detected.

8 Summary, problems and next step

Overall our approach has proven to be quite effective in detecting drinking ADLs. Although the derived values are very simple they show a very high detection rate if combined together. Data acquisition is easy and can be used to improve the models.

There are still some problems left to solve: a key problem is energy management. If WLAN or GPS is active the battery of the smartwatch is empty after several hours which in turn counter fights the idea of a continuous support of its wearer. Sensor reading is not such a battery drain, nevertheless the continuous ADL checking requires processor power. Other problems deal with charging: for elderly people the currently offered charging stations are hard to handle. A key problem is the left vs. right hand wearing of the watch. In order to detect ADLs the user needs to wear the watch on his dominant hand ([2]), otherwise no useful data can be collected. This may require the user to change his watch wearing habits. Data security, rights and laws associated with the gathered data open another problem area. This causes no problems as long as the data are stored and processed within the watch and not sent to portals. But strict legal rules apply if the data are transferred to a central server for further analysis and are made available to others.

We want to improve the app and models so that in the near future the app can be used in daily life. Next planned steps are:

- Currently we use a time frame of ten seconds for the training. This could be lowered to 5 seconds as normally drinking acts are much shorter than 10 seconds. Another option is to reduce the sensor collection interval, e.g. using 100ms instead of 20 milliseconds. This also depends on the smart watch used, some only collect on a fixed time interval.
- Next we intend to collect more data with more persons to check the stability of the model. We also want to explore if there are significant differences between people using their left or right arm as main arm. At the moment we obviously can only detect drinking activities if the watch is worn on the main arm of the user.
- Next we will also implement further models in the real time detection app, e.g. the neural network.
- This will also be tested in connection with questions like user acceptance of smartwatches in general and the acceptance of an app which in a certain way controls and protocols in detail what the user is doing all the day.
- We also need to check the relevance with regard to data security and laws regulating data collection and transmitting it to centralized servers or portals.
- A further idea is to combine the basic weights found with live training to improve detection rate. The user trains the app with drinking ADLs for some time (e.g. with different glasses, bottles and cups). The training data will be used to modify the general weights on a personal basis.
- We intend to broaden the coverage of detectable acts, e.g. tooth brushing, sleeping or eating. The key to get further ADLs classified is the number of training examples for correct classifications. While for some activities this is quite easy (tooth brushing) other activities are harder to experiment with, e.g. tumble detection. Esp. tumble detection is a quite complex ADL as there are many different types of tumbles, from fast tumbles to a more smoothly sliding down.

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