What Are You Doing? Real-Time Activity Recognition using Mobile Phone Sensors

Bernhard Hiesl, Marc Kurz, Erik Sonnleitner

University of Applied Sciences Upper Austria
Faculty for Informatics, Communications and Media
Department of Mobility and Energy
4232 Hagenberg, Austria
email: {firstname.lastname}@fh-hagenberg.at

***Abstract*—This paper focuses on recognizing different activities of people by utilizing the smart-phone as sensor delivering unit. For the sake of simplicity, five different activities (i.e., modes of locomotion) are considered: (i) standing, (ii) walking, (iii) running, (iv) walking upstairs and (v) downstairs. The research challenge is the fact that the phone is placed on the body of the subjects dynamically and orientation independent – thus the system has to adapt autonomously to these characteristics. The sensor data was collected from the built-in accelerometer, gravity and gyroscope sensors of a common smartphone (i.e., Google Pixel XL). The data collection procedure is part of the dynamic placement of this paper addressing position and orientation independent recording and recognizing of activities. Additionally, to acquire full orientation independence, data transformation (horizontal and vertical movement) is applied on the gathered data. Within the framework of this study, five different phone positions are taken into account and are therefore considered in the classification process. To achieve the best approach concerning performance and recognition, different classifiers are evaluated (i.e., (i) k-nearest neighbours (KNN), (ii) Naive Bayes, (iii) Decision Trees and (iv) Random Forest).**

Keywords–Activity recognition; Mobile sensing; Self-adaptation; Adaptive application; Adaptive real-time strategies.

I. INTRODUCTION

This paper is a follow-up of the work-in-progress paper published in 2019 [1]. There, the idea of utilizing smart phones for activity recognition (i.e., gait recognition) in real-time with varying positions of the smart phone has been introduced. Conceptual ideas have been presented – subsequently, this paper focuses on the solution to the problem and the evaluation and results.

The problem statement can be summarized as follows. The major challenge behind this work is the correct detection of people's activities regardless of the mobile phone's position and orientation. In other words, the system should be able to recognize the actual activity of the user by gathering sensor data from the built-in mobile phone sensors only. This should be performed independently of the device's position and orientation - thus being adaptive to contextual details. The changing position and orientation of the mobile phone is also referred to as "dynamic placement" within this paper. To actively detect the activity of a user, an application using a real-time system is required. Therefore, sensor data from the built-in mobile phone sensors need to be collected, processed and classified in real-time. To put it in other words, only a few seconds should be sufficient to detect the activity performed by the user. In detail, the research question can be formulated as follows [1]: *How can highly accurate real-time activity recognition be realized utilizing a dynamically (i.e., rotation, position and orientation independent) on-body placed commercial smartphone?* For the sake of simplicity, five modes of locomotion are specifically considered: (i) standing, (ii) walking, (iii) running, (iv) walking upstairs and (v) downstairs. Generally – as stated in the previous WiP paper [1] – the idea of recognizing activities utilizing commercial smartphones is not new and has been subject to research in numerous publications [2]–[10]. The challenging aspects are the facts that the recognition should be executed at real-time and rotation-, orientation- and position-independent –not forcing the user to conduct an initial calibration.

The WiP paper [1] presented the data collection progress and the accompanying smartphone application allowing for instant labelling of activities upon recording. Additionally, feature extraction methodologies and machine learning models have been evaluated. As related work shows, low level features (e.g., mean, max, min, std deviation, variance, energy, entropy, etc.) are significant enough for activity classification [3][4][10]. To classify the activities correctly and user independently, the system was trained with the help of 15 subjects (10 males and 5 females) and a total sensor data amount of 4 hours and 50 minutes per sensor unit. The focus of this paper is the technical implementation of the autonomous adaptation to the current phone position for the recognition task, as well as the aspect that the recognition should be executed instantly at real-time.

The rest of the paper is structured as follows. Section II (*Methodology & Implementation*) explains the methodological approach to realize the dynamic and orientation independent placement of the phone on the subjects body. Section III (*Results*) summarizes the results achieved during the evaluation. Section IV (*Summary & Outlook*) closes with a summary and an outlook to future work.

II. METHODOLOGY & IMPLEMENTATION

In order to implement the mobile sensing real-time dynamic gait recognition approach, the following steps have to be done: (i) Data Acquisition, (ii) Data Preprocessing, (iii) Feature Extraction, (iv) Model Training. Within the process of the Data Acquisition, subjects are asked to collect sensor data from the built-in mobile phone sensors including the accelerometer, gyroscope and gravity sensor. In the next step, the Data Preprocessing, the gathered data is transformed using a horizontal and vertical movement calculation which is done by utilizing the accelerometer and gravity sensor (orientation

 ISBN: 978-1-61208-781-8

and position independent = dynamic placement). Additionally, the transferred data is ”smoothed” by applying a Savitzky-Golay filter and is then split into smaller data segments using a sliding window approach [11] with an overlap of 50%. The Feature Extraction routine is then used to extract time and frequency domain features. In the last step, a machine learning approach is realized. In total, four different machine learning models are trained offline. These machine learning models are then integrated into the smartphone application for realizing the recognition task. In order to provide a dynamic real-time recognition system using a mobile phone the three steps including (i) Data Acquisition, (ii) Data Preprocessing and (iii) Feature extraction need to be developed within the smartphone application (see WiP paper for further details [1]).

A. Real-Time

Burns and Welling [12] describe the term real-time as the actual response time that a system takes to generate an output from several input values. In other words, it is the actual time it takes to get a result of a system after applying an input. In general, real-time systems can be distinguished between hard and soft real-time systems. In hard real-time systems, a delay of a response can lead to an entire system failure. In soft real-time systems, a delay only degrades the performance of the system. Depending on the place of use, real-time systems can have response times from milliseconds to minutes. By utilizing a technique called sliding window [11] (see Figure 1), the approach in this paper targets a soft real-time activity recognition system with a response time of 2.56 seconds for the first recognition and 1.28 seconds for the following ones. Subsequently, each recognition iteration of the developed real-time approach includes the following steps: (i) gathering 2.56 seconds (time) activity data of a user utilizing mobile phone sensors, (ii) passing the data to the recognition process (input), (iii) performing different calculations on the sensor data and provide the actual gait of the user while performing it (output). Figure 2 shows an example of horizontal and vertical movement within one single window.

Figure 1. Illustration of the sliding window approach.

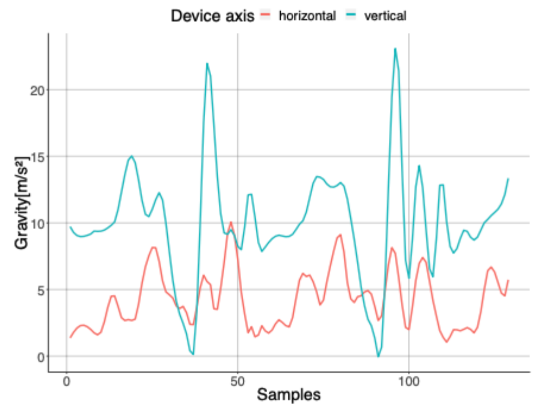

Figure 2. Time series data of a single window showing horizontal and vertical movement.

B. Dynamic Placement

In order to realize the dynamic placement recognition system (position and orientation independent system), the following steps were implemented:

- Sensor recording of activities within several body positions to get position independent data
- Sensor data transformation (horizontal and vertical transformation) to become orientation independent
- Usage of entire recorded and transformed data to train different machine learning models

To be more precise, the first step to achieve a dynamic recognition system was to record sensor data in different pocket locations on the body. In total, five pocket positions are covered in the current version of the system and it was done during the Data Acquisition process (see Figure 3). Within the second step, the sensor data was transformed into a different coordinate system representing the data in horizontal and vertical accelerations. By applying this transformation, the data becomes independent regarding the orientation of the sensing device. The actual transformation is performed using data from the accelerometer and gravity sensor.

After the second step the preprocessed data (transformed, smoothed and segmented data) from different pocked positions was then used to train four different machine learning models. Therefore, the models are ”generalized” concerning pocket positions, because each pocket position is within the ”trained” machine learning model. In other words, the models ”trained” within the training process are all using the same data and therefore do not distinguish between the front right or back left trouser pocket to detect the gait type of a user.

III. Results

Three different testing scenarios were applied to the developed system including environment changes, varying performing speeds and changing positions. Each test scenario is evaluated using gallery dependent (subject within the training set) and independent (subject not inside the training set) sensor data. The goal of the evaluation was to prove that the system is able to classify the activity correctly even despite changing performing parameters. These changing parameters consider a position change of the mobile phone as well as changing speed.

 ISBN: 978-1-61208-781-8

A. Scenarios

1) Environment: The first testing scenario covers the changing of the environment. It is assumed, that the environment during the recognition process can change during or for each execution. In other words, this means that the ideal outcome was to create an environmental independent recognition system. Therefore, the developed recognition system was evaluated using different environments including, different stairs, different floor surfaces and indoor (house) or outdoor environments. The main reason why there is a distinction between an indoor and outdoor environment is that users usually put off their shoes indoors.

The recorded data was only collected from subjects moving forward and straight on a flat surface. The environment testing routine was also performed moving forward and straight only. This environment evaluation is marked as S1 in the system results Section III-C. This environment test was only performed while the phone was in the front right trouser pocket (i) walking on street / grass / indoor, (ii) running on street / grass, (iii) ascending stairs indoor / outdoor, and (iv) descending stairs indoor / outdoor.

2) Speed: Within the second testing scenario covering speed, varying execution speeds are performed and evaluated on the activity recognition system. However, the freedom of the actual execution speed within this evaluation is limited in terms of direction. In other words, the subjects participating in the evaluation of the system are only able to change the speed, not altering the motion process of walking itself in an abnormal or directional way. This is because the data within the training set only provides motion data in that recognizes forward direction limiting the evaluation itself in terms of direction. To be more precise, the speed test investigates the correct classification if there are changes regarding the walking speed. This is possible, because subjects within the training set have already personal speed interpretations performing the activities. For example, participant P1 walks with a speed of 3 km/h, whereas participant P2 walks with a speed of 3.6 km/h. Both participants perform the gait ”walking”, but at individual pace. Therefore, the system should still recognize the gait correctly with varying speeds. Another example, could be running or climbing stairs where each participant executes the activity at a different pace. Within the result overview Section III-C, this execution evaluation scenario is marked as S2. The speed adjustment evaluation consists of the following test cases where the phone was placed in the front right trouser pocket: (i) walking slow / normal / fast, (ii) running slow / normal / fast, (iii) ascending stairs slow / normal / fast, and (iv) descending stairs slow / normal / fast.

3) Position: In order to fulfil the main focus of this paper – the dynamic placement of the mobile phone – the third evaluation scenario addresses the position evaluation. It is used to evaluate the correct recognition performance of the system regardless of the device's orientation. Nevertheless, there are limitations concerning the mobile phone placement during the evaluation. The current version of the system only supports gait recognition within five mobile phone positions including the two front trouser pockets, the two back trouser pockets and the chest pocket of a shirt or the inner jacket pocket (see Figure 3). In Section III-C the position evaluation scenario is marked as S3.

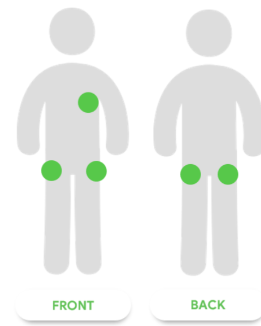

Figure 3. Relevant pocket positions within the position evaluation.

B. Participants

Within the entire evaluation process, two subjects were asked to participate in the process of testing the system. This was one of the most important parts of the evaluation, because the system should either work with participants which are inside the training set (i.e., gallery dependent) or participants not enrolled within the training process (i.e., gallery independent). In other words, gallery dependent participants are testing subjects, which are known by the machine learning model. In contrast, participants which are gallery independent are test subjects which are not known by the trained machine learning model beforehand. The gallery dependent tests are annotated as *S1D* (environment), *S2D* (speed) and *S3D* (position) depending on the test scenario. Accordingly, the tests for the gallery independent cases are marked with *S1I* (different environments), *S2I* (different execution speeds) and *S3I* (the varying position evaluation).

C. Result Overview

The system is evaluated applying two cases: (i) offline (by using newly recorded data and performing recognition offline) and (ii) online (at real-time) using sensor data processed in real-time on the smart-phone. Therefore, the results for the offline and online cases are presented in the following two Sections III-C1 and III-C2.

1) Offline Evaluation: The offline evaluation process uses a computer to recognizing the actual gait of newly provided sensor data from a subject performing different activities. It is done by creating sensor data which is not covered by the training data applied during the machine learning model creation. Therefore, a subject gallery dependent and a subject gallery independent were asked to record new sensor data with changing environments, speeds and mobile phone positions. In the next step, the data is transferred to a computer to evaluate the different machine learning models. The following Tables I to III summarize the accuracies for the cases *S1D*, *S2D* and *S3D* (gallery dependent case).

TABLE I. RECOGNITION ACCURACIES FOR *S1D* (ENVIRONMENT).

Model	Grass	Street	Outdoor	Indoor	Combined
KNN	91.6%	100%	100%	93.75%	96.1%
Naive Bayes	97.2%	100%	88.8%	93.75%	94.8%
Decision Tree	94.4%	100%	100%	91.6%	96.1%
Random Forest	94.4%	100%	100%	95.8%	97.4%

 ISBN: 978-1-61208-781-8

TABLE II. RECOGNITION ACCURACIES FOR *S2D* (SPEED).

Model	Slow	Normal	Fast	Combined
KNN	80.0%	98.3%	91.6%	90.0%
Naive Bayes	83.3%	100%	55.0%	79.4%
Decision Tree	88.3%	91.6%	75.0%	85.0%
Random Forest	96.6%	100%	86.6%	94.4%

The abbreviations used in Table III have the following meaning: (i) FC = front chest, (ii) FR = front right trouser pocket, (iii) FL = front left trouser pocket, (iv) BR = back right trouser pocket and (v) BL = back left trouser pocket (see also Figure 3).

TABLE III. RECOGNITION ACCURACIES FOR *S3D* (POSITION).

Model	FC	FR	FL	BR	BL	Combined
KNN	86.6%	100%	100%	100%	100%	97.6%
Naive Bayes	80.0%	98.3%	100%	96.6%	100%	95.0%
Decision Tree	88.3%	88.3%	100%	90.0%	95.0%	92.3%
Random Forest	86.6%	100%	100%	93.3%	100%	96.0%

The gallery independent case (the system is evaluated with data of a person that is not included in the training set) is more meaningful. It proves that the system is also capable of recognizing activities from any person at an acceptable accuracy. The following Tables IV to VI summarize the accuracies for the cases *S1I*, *S2I* and *S3I* (gallery independent case).

TABLE IV. RECOGNITION ACCURACIES FOR *S1I* (ENVIRONMENT).

Model	Grass	Street	Outdoor	Indoor	Combined
KNN	83.3%	100%	100%	100%	97.4%
Naive Bayes	100%	100%	86.1%	81.2%	91.0%
Decision Tree	77.7%	94.4%	91.6%	91.6%	89.1%
Random Forest	94.4%	100%	100%	100%	98.7%

TABLE V. RECOGNITION ACCURACIES FOR *S2I* (SPEED).

Model	Slow	Normal	Fast	Combined
KNN	93.3%	100%	96.6%	96.6%
Naive Bayes	81.6%	91.6%	61.6%	78.3%
Decision Tree	75.0%	91.6%	100%	88.8%
Random Forest	96.6%	100%	91.6%	96.1%

The following Figure 4 shows the results of the gallery dependent test scenarios whereas Figure 5 displays gallery independent results of each test scenario. As shown in Figure 4, the Random Forest algorithm performs best regarding environment changes (97.4%) and speed adjustments (94.4%), whereas the KNN algorithm achieves the highest accuracy of 97.6% in the last position evaluation. Figure 5 displays the recognition accuracy rates of a subject which is not considered in the training set. Even though the activity data provided by the subject was not used to train the model, the accuracy rates are very similar to the accuracy rates shown in the gallery dependent evaluation test. The highest precision of 98.7% was achieved by applying the environment evaluation on the Random Forest classifier followed by the KNN model evaluating the speed adjustment by reaching an accuracy of 96.6%. In the last evaluation scenario (position), the KNN and Random Forest algorithm achieved a recognition rate of 94%.

TABLE VI. RECOGNITION ACCURACIES FOR *S3I* (POSITION).

Model	FC	FR	FL	BR	BL	Combined
KNN	91.6%	100%	96.6%	83.3%	98.3%	94.0%
Naive Bayes	71.6%	91.6%	88.3%	83.3%	90.0%	85.0%
Decision Tree	71.0%	91.6%	93.3%	93.3%	91.6%	88.0%
Random Forest	71.6%	100%	98.3%	100%	100%	94.0%

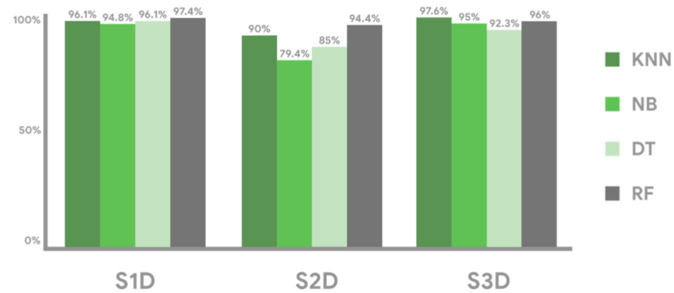

Figure 4. Recognition accuracies of each machine learning model (K-nearest Neighbour, Naive Bayes, Decision Tree and Random Forest) applying the offline gallery dependent scenarios evaluation including environment, speed and position changes.

2) Online Evaluation: In contrast to the offline evaluation, a real-time/online evaluation was carried out within this paper. The real-time evaluation is supported by the developed smart phone application. Instead of labelling and transferring sensor data to a computer, the application collects sensor data of the subject performing an activity, preprocesses it, extracts time and frequency domain features and classifies the actual activity/gait in real-time utilizing machine learning models which were integrated into the application beforehand. In order to decrease the effort of the evaluation process including testing different machine learning models, the application was extended to provide a ”ground truth”. In other words, the resulting feature vector provided by the smart phone application was extended with the actual gait type the subject was performing. The feature vector containing the ground truth was then used to evaluate the machine learning models on the computer. However, all evaluation scenarios were performed by using the machine learning models on the mobile device itself. The following Tables VII to IX summarize the accuracies for the cases *S1D*, *S2D* and *S3D* (gallery dependent case), whereas For the real-time (online) environment evaluation a gallery dependent subject performed the exact same testing routine, which was executed during the offline environment evaluation.

TABLE VII. RECOGNITION ACCURACIES BASED ON ENVIRONMENT CHANGES (*S1D*) OF A PERSON INSIDE THE TRAINING DATA FOR THE ONLINE CASE.

Model	Grass	Street	Outdoor	Indoor	Combined
KNN	97.2%	100%	100%	95.8%	98.0%
Naive Bayes	100%	100%	83.3%	83.3%	91.0%
Decision Tree	100%	97.2%	100%	89.5%	96.1%
Random Forest	100%	100%	100%	100%	100%

The next evaluation step were the gallery independent evaluation scenarios, which means that a subject, whose data was not taken into account within the training, provided the real-time sensor data for the online evaluation of the

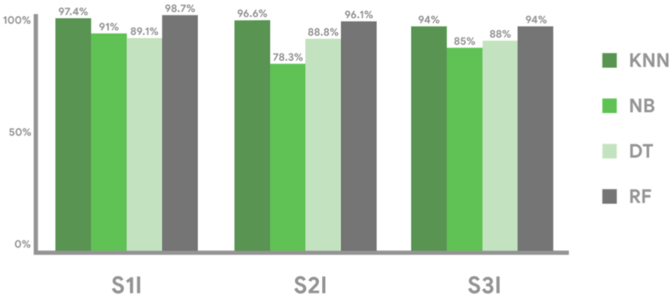

Figure 5. Recognition accuracies of each machine learning model (K-nearest Neighbour, Naive Bayes, Decision Tree and Random Forest) applying the offline gallery independent scenarios evaluation including environment, speed and position changes.

TABLE VIII. RECOGNITION ACCURACIES BASED ON SPEED CHANGES (*S2D*) OF A PERSON INSIDE THE TRAINING DATA FOR THE ONLINE CASE.

Model	Slow	Normal	Fast	Combined
KNN	96.6%	100%	73.3%	89.4%
Naive Bayes	80.0%	90.0%	48.3%	72.7%
Decision Tree	80.0%	98.3%	68.3%	82.2%
Random Forest	96.6%	100%	83.3%	93.3%

recognition system. The smartphone application was used to record, preprocess and classify sensor data in real-time. The following Tables X to XII summarize the accuracies for the cases *S1I*, *S2I* and *S3I* (gallery independent case) for the online scenario.

Figure 6 shows the accuracies of the different gallery dependent evaluation scenarios including environment (S1D), speed (S2D) and position (S3D) for each machine learning model whereas Figure 7 shows the accuracies of the gallery independent evaluation scenarios (environment, speed and position). As shown in Figure 6, the Random Forest algorithm achieved an accuracy of 100% using gallery dependent sensor data on the evaluation test scenario, whereas utilizing activity motion data from a subject, whose data is not in the training set, the accuracy reaches 97.4% (Figure 7). Due to fact of high accuracies in both evaluations (gallery dependent and independent), it can be said that the real-time recognition system is independent of environment changes and users. The second evaluation scenario is the the speed adjustment evaluation (S2D and S2I). In other words, the correct detection of the gait regarding pace changes utilizing different machine learning models. As shown in the bar charts of Figure 6 and Figure 7 the overall accuracies decrease. This is because slower and faster motions can lead to incorrect classifications. For example, if a user is walking faster than usual the classification process can lead to incorrect results. Nevertheless, the highest accuracy of 97.2% concerning execution speed changes was achieved by the Random Forest algorithm during the real-time speed gallery independent evaluation. The last position evaluation scenario that was compared is shown as well (S3D and S3I). Even though the position of the phone changes between the front chest, front right, front left, back right and back left pocket, the KNN algorithm of the gallery dependent or the Random Forest of the gallery independent test evaluation achieved high recognition rates (KNN= 94.6% and RF = 95.3%). The other algorithms including the Naive Bayes and Decision Tree detect the gait types between an accuracy rate of 85% and 90.3%. All in all it can be said, that the developed recognition system is able to detect the actual gait of a user dynamically. It is capable of detecting the activity regardless the phone position and orientation, is user independent and recognizes gait types in real- time (within 2.56 seconds for the first recognition) with a satisfying result.

TABLE IX. RECOGNITION ACCURACIES BASED ON DIFFERENT BODY POSITIONS (*S3D*) OF A PERSON INSIDE THE TRAINING DATA FOR THE ONLINE CASE.

Model	FC	FR	FL	BR	BL	Combined
KNN	85.0%	100%	100%	96.6%	95.0%	94.6%
Naive Bayes	80.0%	90.0%	95.0%	90.0%	96.6%	90.3%
Decision Tree	86.6%	98.3%	86.6%	83.3%	96.6%	90.3%
Random Forest	88.3%	100%	100%	90.0%	93.3%	94.3%

TABLE X. RECOGNITION ACCURACIES BASED ON ENVIRONMENT CHANGES (*S1I*) OF A SUBJECT NOT CONSIDERED IN THE TRAINING DATA FOR THE ONLINE CASE.

Model	Grass	Street	Outdoor	Indoor	Combined
KNN	97.2%	97.2%	97.2%	97.9%	97.4%
Naive Bayes	97.2%	100%	77.7%	54.1%	80.1%
Decision Tree	91.6%	80.5%	94.4%	83.3%	87.1%
Random Forest	97.2%	97.2%	100%	95.8%	97.4%

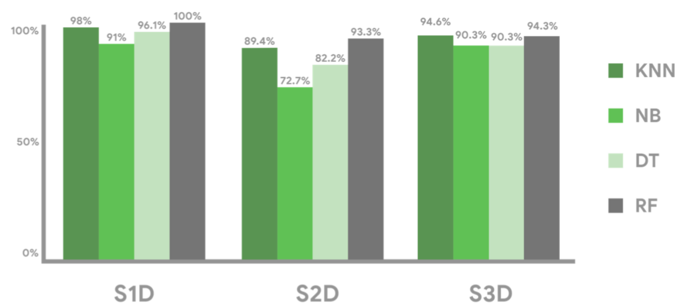

Figure 6. Recognition accuracies of each machine learning model (K-nearest Neighbour, Naive Bayes, Decision Tree and Random Forest) applying the online gallery dependent scenarios evaluation including environment (S1D), speed (S2D) and position (S3D) changes.

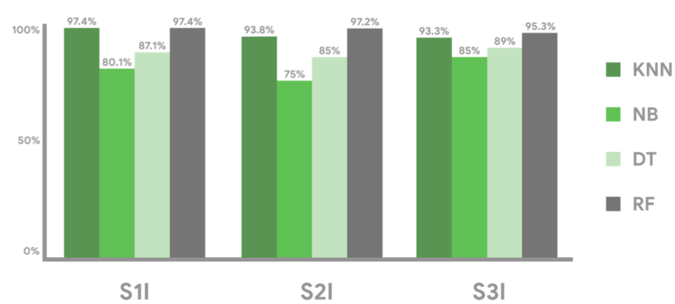

Figure 7. Recognition accuracies of each machine learning model (K-nearest Neighbour, Naive Bayes, Decision Tree and Random Forest) applying the online gallery in- dependent scenarios evaluation including environment (S1D), speed (S2D) and position (S3D) changes.

TABLE XI. RECOGNITION ACCURACIES FOR *S21* (SPEED).

Model	Slow	Normal	Fast	Combined
KNN	93.3%	98.3%	90.0%	93.8%
Naive Bayes	88.3%	85.0%	51.6%	75.0%
Decision Tree	80.0%	91.6%	83.3%	85.0%
Random Forest	98.3%	98.3%	95.0%	97.2%

TABLE XII. RECOGNITION ACCURACIES FOR *S31* (POSITION).

Model	FC	FR	FL	BR	BL	Combined
KNN	90.0%	98.3%	98.3%	93.3%	86.6%	93.3%
Naive Bayes	80.0%	85.0%	98.3%	78.3%	83.3%	85.0%
Decision Tree	91.6%	91.6%	88.3%	86.6%	86.6%	89.0%
Random Forest	88.3%	98.3%	96.6%	93.3%	100%	95.3%

IV. CONCLUSION

To summarize, the aim to create a system, which is able to adaptively recognize activities regardless the position and orientation of the recording device (i.e., commercial smartphone) with built-in motion sensors was achieved with a recognition accuracy of 96.1%. Activity recognition systems apply supervised classification machine learning approaches in order to ”classify” (detect) an actual activity on new data provided by users. In total, 15 subjects were asked to participate in the data acquisition process where motion data from the accelerometer, gravity, linear accelerometer and gyroscope sensor was collected. Each subject provided sensor data from five different body positions (position independence) as well as five different activities. To achieve orientation independence, the gathered data was transformed into another coordinate system (horizontal and vertical movements). Additionally, the second preprocessing step was the usage of the Savitzky-Golay filter in order to ”smooth” the data while preserving high and low signal peaks. Furthermore, data segmentation (sliding window) was applied on the transformed and smoothed data in order to realize a real-time approach. The sliding window of the recognition system has the length of 2.56 seconds and an overlap of 50%. In the next step, the segmented data was then passed to the feature extraction routine in order to derive time and frequency domain features. The last step was the machine learning model creation. In order to find the best machine learning model concerning performance and accuracy, four different algorithms (i.e., k-nearest Neighbour, Naive Bayes, Decision Tree and Random Forest) were compared and integrated into the implemented smartphone application. Subsequently, the real-time dynamic gait recognition system was evaluated using 12 different evaluation scenarios. Half of the evaluation scenarios were taken offline on the computer and the other half was performed online using the smartphone application. The activity recognition system was tested on subjects which are gallery dependent (data included in the training set) and gallery independent (data not included in the training set). To underline the hypothesis concerning the dynamic placement, the recognition system was tested on recognizing the actual gait in five different body positions. The best overall recognition accuracy (offline and online evaluation combined) of 96.1% was achieved by the Random Forest algorithm, which turns out to be the most suitable algorithm for the developed system. Overall, it can be said that the developed real-time dynamic gait recognition system running on a smartphone is able to detect the actual activities (i.e., the gait) of a user regardless the position and orientation of the device with an recognition accuracy of up to 96.1%. Having proven the feasibility of developing a gait recognition system which is position and orientation independent it is legitimate to state that the system could be hugely beneficial to tracking and analysing human activity in different commercial use-cases (e.g., physiotherapy, elderly care, industrial manufacturing, etc.).

The Feature Extraction process applied within this paper uses standard mathematical features and includes among other things maximal, minimal, mean, standard deviation values from time and frequency domains. Although standard mathematical features are applied, the current version of the real-time dynamic recognition system achieves a satisfyingly result. However, the feature extraction process could be further improved by using more ”complex” features (e.g., signal peaks in time domain) or utilizing different feature selection approaches (e.g., grid search or relief). For example, by applying a grid search on the current feature vector (177 features), the number of significant features for the classification process could be improved and therefore most likely increase the performance.

ACKNOWLEDGMENT

This paper and all corresponding results, developments and achievements are a result of the Research Group for Secure and Intelligent Mobile Systems (SIMS).

REFERENCES

[1] M. Kurz, B. Hiesl, and E. Sonnleitner, “Real-time activity recognition utilizing dynamically on-body placed smartphones,” in The Eleventh International Conference on Adaptive and Self-Adaptive Systems and Applications (ADAPTIVE 2019), 2019, pp. 84–87.

[2] A. Anjum and M. U. Ilyas, “Activity recognition using smartphone sensors,” 2013 IEEE 10th Consumer Communications and Networking Conference (CCNC), 2013, pp. 914–919.

[3] X. Su, H. Tong, and P. Ji, “Activity recognition with smartphone sensors,” Tsinghua science and technology, vol. 19, no. 3, 2014, pp. 235–249.

[4] L. Bao and S. S. Intille, “Activity recognition from user-annotated acceleration data,” in International Conference on Pervasive Computing. Springer, 2004, pp. 1–17.

[5] G. Bieber, J. Voskamp, and B. Urban, “Activity recognition for everyday life on mobile phones,” in International Conference on Universal Access in Human-Computer Interaction. Springer, 2009, pp. 289–296.

[6] M. Derawi and P. Bours, “Gait and activity recognition using commercial phones,” computers & security, vol. 39, 2013, pp. 137–144.

[7] Y. He and Y. Li, “Physical activity recognition utilizing the built-in kinematic sensors of a smartphone,” International Journal of Distributed Sensor Networks, vol. 9, no. 4, 2013, p. 481580.

[8] A. Henpraserttae, S. Thiemjarus, and S. Marukatat, “Accurate activity recognition using a mobile phone regardless of device orientation and location,” in Body Sensor Networks (BSN), 2011 International Conference on. IEEE, 2011, pp. 41–46.

[9] M. Kurz, “Opportunistic activity recognition methodologies,” Ph.D. dissertation, Johannes Kepler University Linz, Jun. 2013.

[10] J. R. Kwapisz, G. M. Weiss, and S. A. Moore, “Activity recognition using cell phone accelerometers,” ACM SigKDD Explorations Newsletter, vol. 12, no. 2, 2011, pp. 74–82.

[11] L. Sun, D. Zhang, B. Li, B. Guo, and S. Li, “Activity recognition on an accelerometer embedded mobile phone with varying positions and orientations,” in International conference on ubiquitous intelligence and computing. Springer, 2010, pp. 548–562.

[12] A. Burns and A. J. Wellings, Real-time systems and programming languages: Ada 95, real-time Java, and real-time POSIX. Pearson Education, 2001.