Optimal Sensor Placement for Human Activity Recognition with a Minimal Smartphone–IMU Setup

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Abstract: Human Activity Recognition (HAR) of everyday activities using smartphones has been intensively researched over the past years. Despite the high detection performance, smartphones can not continuously provide reliable information about the currently conducted activity as their placement at the subject's body is uncertain. In this study, a system is developed that enables real-time collection of data from various Bluetooth inertial measurement units (IMUs) in addition to the smartphone. The contribution of this work is an extensive overview of related work in this field and the identification of unobtrusive, minimal combinations of IMUs with the smartphone that achieve high recognition performance. Eighteen young subjects with unrestricted mobility were recorded conducting seven daily-life activities with a smartphone in the pocket and five IMUs at different body positions. With a Convolutional Neural Network (CNN) for activity recognition, activity classification accuracy increased by up to 23% with one IMU additional to the smartphone. An overall prediction rate of 97% was reached with a smartphone in the pocket and an IMU at the ankle. This study demonstrated the potential that an additional IMU can improve the accuracy of smartphone-based HAR on daily-life activities.

1 INTRODUCTION

Human Activity Recognition (HAR) enables retrieval of high-level knowledge from low-level sensor inputs (Chen et al., 2019) and is capable of monitoring daily-life activities as walking, sitting, or running. Important applications lay in the field of healthcare in terms of physical monitoring (Zhang and Sawchuk, 2012). For example, HAR can inform subjects about irregularities as early as possible for diagnosis and direct treatments.

HAR is commonly performed using inertial measurement units (IMUs). An IMU is a combination of multiple inertial sensors: an accelerometer (measures acceleration), a gyroscope (measures angular velocity), and sometimes a magnetometer (measures magnetic field) (Ahmad et al., 2013). An IMU can be used as a standalone device or integrated into other devices like smartphones. Recent advancements in hardware and a growing variety of standalone IMU devices (Zhou et al., 2020) led to increasing applications using IMUs (Zhu and Sheng, 2009). The fact that many of them now also support wireless communication protocols allows smartphones or computers to receive sensor data in real-time. Meanwhile, smartphone-based HAR has been intensively researched over the past years. Because smartphones require no installation costs, are user-friendly, and provide an unobtrusive way of recording data in daily situations, they have become a standard tool for HAR (Su et al., 2014).

To date, a large number of studies exist investigating HAR. Some of them focus on HAR using smartphone sensors (Su et al., 2014; Ghosh and Riccardi, 2014; Bayat et al., 2014) and others on HAR using body-worn standalone IMU devices (Altun and Barshan, 2010; Huynh, 2008; Janidarmian et al., 2017), few of them transferring data via Bluetooth (Bulling et al., 2014; Khan et al., 2010). There have also been some studies determining the highest accuracy-achieving sensor placements (Atallah et al., 2011; Orha and Oniga, 2014; Mannini et al., 2015).

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1.1 Motivation

Smartphones as recording devices are a convenient solution for HAR as they have built-in motion sensors such as accelerometer or gyroscope. However, the sensor data received from smartphones might also be incorrect or misleading in many situations, even if only considering all the different ways people carry their phones or how they interact with them during the day. Activities such as writing a short text message and holding it in the hand, laying it on a table, or putting it in another pocket are just a few examples where correct activity recognition is more difficult.

Another important requirement for HAR is to enable the observed subjects to behave as naturally as possible. This can not be achieved if the complete body is covered with sensors, because this setup would only work for short term applications as in a hospital setting, but not for everyday activities. A system that addresses these problems and enables high accuracy HAR directly from the smartphone of the subject is needed.

1.2 Contribution

In this paper, an activity recognition system is presented. Its main contribution was the determination of an optimal minimum smartphone and IMU sensor setup improving HAR results for basic daily-life activities. This work's concrete contributions are as follows:

- A dataset of 18 participants performing seven different every-day activities was collected in an experiment (Section 3). To the best of our knowledge, this is the first study combining Bluetooth sensors with internal smartphone sensors data collection for HAR.
- It was proved that the HAR performance of the smartphone in the subject's pocket could be improved by 23% if combined with a body-worn standalone IMU device. The highest improvements are reached by the ankle and the lower back. F1-scores of up to 97% are reached using a Convolutional Neural Network (Section 4.4).
- Also, it was shown that some single IMU placements achieve high recognition precisions (F1-scores around 87%), making the resulting recognition more independent from the smartphone in case it produces imprecise data (Section 4.4).

Beginning with an introduction of daily-life activity recognition in related work by giving an overview of similar studies and their applied methods (Section 2), followed by a description of the conducted experiment (Section 3) and its evaluation (Section 4), this work concludes by discussing future research (Section 5).

2 RELATED WORK

2.1 Background

The recognition of daily life human activities is a popular problem. There are several common approaches and varying factors such as probed activities and chosen sensor setups. This section provides a review of methods for HAR with a special focus on daily-life activity recognition.

2.1.1 Human Activity Recognition Process

A basic *Activity Recognition Process* (ARP) consists of five steps. Data is *collected* from sensor signals. The acquired data might consist of artifacts arising from malfunctions, simultaneously occurred physical activities or electronic fluctuations. Thus, the data is *preprocessed*. It is *segmented* into windows of a specific length and labeled with the activity that was conducted in this segment. In the next step, every time window is transformed into a vector of features (Dehghani et al., 2019). In *Feature extraction* for HAR, it is challenging to produce distinguishable features due to the similarity of activities that might share similar characteristics (e.g. walking and running) (Chen et al., 2020). Finally, based on the data and its corresponding labels, a *classifier* is trained. According to (Dehghani et al., 2019), Decision Tree, Naïve Bayes, Support vector machine, K-nearest neighbors, Hidden Markow Models, and ensemble classifiers as Random Forest are common and preferred classifiers in HAR.

2.1.2 Activities

According to Table 1 and Table 2, activity sets in similar studies often include walking, sitting, and standing, sometimes combined with primary activities as eating or vacuuming. Some studies investigated even more complex daily-life activities, for instance, (Atallah et al., 2011) the wiping of tables or (Valarezo et al., 2017) the folding of laundry.

2.1.3 Inertial Sensors

In (Zhang and Sawchuk, 2012), the accelerometer proved to be the best performing motion sensor to recognize sitting, walking, climbing upstairs and

Table 1: Related work determined the best sensor positions for specific activities using accelerometers or IMUs.

	Activities	**Best Positions**
(Atallah et al., 2011)	lying down	wrist
	preparing food, eating and drinking, socializing, reading, getting dressed	waist
	walking, treadmill walking, vacuuming, wiping tables	chest, wrist
	running, treadmill running, cycling	ear, arm, knee
	sitting down and getting up, lying down and getting up	waist, chest, knee
(Orha and Oniga, 2014)	standing, sitting, supine, prone, left lateral recumbent, right lateral recumbent, walking, running, forward/left/right bending, squats, settlements and lifting the chair, falls, turn left and right, upstairs, downstairs	right thigh, right hand
(Bao and Intille, 2004)	ambulation, posture	thigh, hip, ankle
	upper body movements (sitting, reading, watching TV)	wrist, arm
	total of 20 everyday activities	thigh, wrist / hip, wrist
(Mannini et al., 2015)	walking	ankle, thigh
(Bulling et al., 2014)	opening/closing window, watering plant, reading, drinking a bottle, cutting/chopping with a knife, stirring in a bowl, forehand, backhand, smash	wrist

downstairs, riding the elevator up and down, and brushing teeth. To detect falling, the rotation angle retrieved from the gyroscope increases the performance. Therefore, the accelerometer and gyroscope improve the reliability of the recognition process by complementing each other. The researchers in (Shoaib et al., 2013) determined that climbing upstairs has a high recognition accuracy by a gyroscope at most positions while for example standing is better recognized by an accelerometer. They also showed that the magnetometer has a high dependence on directions and is thus causing over-fitting in training classifiers (Shoaib et al., 2013).

2.1.4 Sensor Setup

The results of an ARP heavily depend on the chosen sensor placements (Mohamed et al., 2018). An overview of related work examining best achieving sensor positions using accelerometers can be found in Table 1. For basic daily life activities, placements on the wrist, the knee, the waist, and the thigh seem to provide high classification accuracy. As for the referenced studies, a combination of arm and leg covers most of the activities. As of (Bao and Intille, 2004), complex activities require at least one sensor on the upper and one on the lower body.

Typical frequencies for daily activities are for example 27 Hz (Orha and Oniga, 2014), 30 Hz (Figueira et al., 2016), 32 Hz (Bulling et al., 2014), 50 Hz (Dehghani et al., 2019), or 100 Hz (Gao et al., 2019). (Mannini et al., 2015) sampled walking data down to 30 Hz and did not see a difference in recognition accuracy. In (Ghosh and Riccardi, 2014) the classification accuracy drops significantly for sampling rates lower than 10 Hz.

2.1.5 Data Preprocessing

The chosen window can vary in size and can be either overlapping or non-overlapping. (Dehghani et al., 2019) found, that when subject-independent cross-validation is used, the performance of HAR systems can not be improved by using overlapping sliding windows instead of non-overlapping windows. The window size has a significant influence on the accuracy of the ARP. To be able to differentiate the activity from others, the window should include at least one instance of the activities' repeating action such as *taking a step* for walking. On the other hand, an increased window size does not necessarily improve recognition performance (Janidarmian et al., 2017). As of (Banos et al., 2014), the most accurate detection is achieved with short windows of two seconds or smaller, very short windows ($0.25-0.5$ s) lead to a very good recognition performance.

2.2 Overview of Related Work

As already mentioned in Section 1, there have been a lot of studies regarding HAR. In Table 1, there has been presented an excerpt of studies investigating optimal sensor combinations for accelerometers as well as IMUs. In the following, a short survey of further studies dealing with daily-life activity recognition is given. Table 2 presents a more detailed overview.

A large number of studies aimed to distinguish between different activities by using one or multiple ac-

Table 2: Overview of HAR studies using accelerometers and HAR studies using IMUs.

	Accelerometer Placements (total number)	**Activities (total number)**	**Sampling Rate**	**Subj.**	**(Best) Method**	**Accur.**
(Foerster et al., 1999)	sternum, wrist, thigh, lower leg (5)	sitting, standing, lying, sitting and talking, working at keyboard, walking, stairs up, stairs down, cycling (9)	16 Hz	24	template matching	95.8%
(Mantyjarvi et al., 2001)	3 left hip, 3 right hip (6)	walking, upstairs, downstairs, opening doors (4)	256 Hz	6	independent component analysis	83% – 90%
(Bao and Intille, 2004)	hip, wrist, upper arm, ankle, thigh (5)	walking, sitting, standing, watching TV, running, stretching, scrubbing, folding laundry, brushing teeth, riding elevator, riding escalator, climbing stairs, walking carrying items, working on computer, eating or drinking, reading, cycling, strength-training, vacuuming, lying down (20)	76.25 Hz	20	decision tree classifiers	84%
(Tapia et al., 2007)	hip, thigh, ankle, upper arm, wrist (5)	*in different variations:* lying down, standing, sitting, walking, running, climbing stairs, cycling, carrying weight, moving weight, and more gym activities (30)	30 Hz	21	C4.5 classifier	94.9%
(Krishnan and Panchanathan, 2008)	hip, ankle, thigh (3)	walking, sitting, standing, running, cycling, lying, climbing stairs (7)	76.25 Hz	20	AdaBoost	93%
(Bonomi et al., 2009)	lower back (1)	lying, sitting, working on computer, standing, washing dishes, walking, downstairs, upstairs, walking outside, running, cycling (11)	20 Hz	20	decision tree classifiers	93%
(Mannini and Sabatini, 2010)	hip, wrist, arm, ankle, thigh (5)	walking, sitting, standing, running, cycling, lying, climbing stairs (7)	76.25 Hz	20	NM classifier	98.5%
(Mannini et al., 2015)	ankle, thigh, hip, arm, wrist (5)	lying, sitting, sorting files on paperwork, cycling, natural walking, treadmill walking, carrying a load, stairs or elevator, jumping-jacks, sweeping with a broom, painting with roller/brush (28)	90 Hz	33	cross-validation with SVM	91.2%
(Janidarmian et al., 2017)	waist, lower arms, upper arms, lower legs, upper legs, chest (10)	combined datasets (70)	8 - 100 Hz	228	principal component analysis	96.44% ± 1.62%

	IMU Placements (total number)	**Activities (total number)**	**Sampling Rate**	**Subj.**	**(Best) Method**	**Accur.**
(Altun and Barshan, 2010)	chest, arms, legs (5)	sitting, standing, lying down on back/right side, upstairs, downstairs, standing/moving in elevator, walking, walking on treadmill, running on treadmill, exercise on stepper/cross trainer, cycling, rowing, jumping, playing basketball (19)	25 Hz	8	BDM classification	95%
(Zebin et al., 2016)	pelvis, thighs, shanks (5)	walking, upstairs, downstairs, sitting, standing, lying down (6)	50 Hz	12	Convolutional Neural Network	97.01%
(Rivera et al., 2017)	wrist (1)	open door, close door, open fridge, close fridge, clean table, drink from cup (8)	100 Hz	12	Recurrent Neural Network	80.09%
(Valarezo et al., 2017)	wrist (1)	lying, sitting, standing, walking, running, cycling, Nordic walking, ironing, vacuuming, rope jumping, upstairs, downstairs, *optional:* watching TV, computer work, driving car, folding laundry, cleaning house, playing soccer (12/6)	100 Hz	9	Recurrent Neural Network	96.95%

celerometers. (Foerster et al., 1999) for example as one of the earliest works on this topic dealt with 5 accelerometers attached to 24 subjects to recognize postures and motions by using a hierarchical classification model resulting in an accuracy of 95.8%. On only four basic activities performed by six participants, (Mantyjarvi et al., 2001) reached an overall recognition accuracy of $83\% - 90\%$. With 93%, (Bonomi et al., 2009) accomplished a bit higher recognition performance on seven more activities and only one accelerometer placed at the lower back. (Bao and Intille, 2004) equipped the body with 5 accelerometers at the hip, wrist, upper arm, ankle, and thigh to differentiate between 20 activities performed by 20 subjects, resulting in a similar performance using decision tree classifiers. From the generated dataset by (Bao and Intille, 2004), 3 accelerometers have been selected to recognize seven lower body activities in (Krishnan and Panchanathan, 2008). The accuracy reached 93%. (Mannini and Sabatini, 2010) applied several learning methods on the same dataset excerpt, but with additional wrist and arm sensor and achieved an accuracy of 98.5%. In (Janidarmian et al., 2017), several datasets have been combined to generate a dataset consisting of 70 activities performed by 228 subjects, recorded by 10 accelerometers covering most relevant body positions. The results are impressive as an accuracy of $96.44\% \pm 1.62\%$ was achieved using a principal component analysis.

While the accelerometer provides good results as seen for the previously introduced studies, IMU sensors also come with an additional gyroscope and magnetometer. Instead of single accelerometers, few studies used an IMU sensor and achieved high recognition performances. (Altun and Barshan, 2010) retrieved 95% from five IMUs placed at the chest and each leg and arm. Eight subjects had conducted 19 activities, including standard activities but also rowing, jumping, and playing basketball. The single IMU setup on the participant's wrist was tested by (Rivera et al., 2017) as well as (Valarezo et al., 2017). Latter retrieved 96.95% accuracy on 18 different activities performed by nine subjects. (Zebin et al., 2016) used a Convolutional Neural Network with an accuracy of 91.01% when recognizing walking, upstairs, downstairs, sitting, standing, and lying down composed by 12 subjects from five IMUs.

2.3 Learnings from Related Work

To summarize, there have already been studies investigating HAR using accelerometers and IMUs, mostly reaching a recognition accuracy between 80% and 97%. Thus, IMUs seem to be sufficient for recognizing basic daily-life activities. There were also works comparing different combinations for specific activities to find out about optimal sensor positions, sampling rates, and window sizes. It appears that the optimal combinations heavily depend on the conducted activities.

Optimal sensor positions were aimed to be found in related work for independent accelerometer or IMU setups, but having the smartphone in the pocket as a fixed sensor and testing the improvement of a combination was not considered.

Besides, to provide HAR from IMUs on the body, a device capable of complex computations and providing enough storage is required. The data transfer in the above-mentioned studies mostly happened between the IMUs and a computer to avoid processing and storage restrictions of other devices as smartphones. Thus, a computer or even a wire must be present, which does not allow the natural conduction of daily activities.

The contribution of this work is to investigate the influence of different IMU positions for smartphone-based HAR.

3 EXPERIMENTAL SETUP

3.1 Recording Sequence

Following related work, the most commonly investigated daily activities were selected: *lay, sit, stand, walk, climb upstairs, climb downstairs, and run*.

To collect comparable data, a recording sequence was created. Every subject performed this sequence at a stretch with short pauses between the different activities. The pauses were needed for (1) a more efficient data segmentation and (2) giving the subjects enough time to reach the next "station" (for example the chair to sit). See Table 3 for the complete sequence. Manual adjustment of the labeled data was not necessary due to the strict schedule.

The experiment was carried out in the foyer of a building and the open area in front of it. Sitting, lying, standing, walking, and running were easy to realize using chairs, tables, and a mat. For the stair climbing activities, a long staircase consisting of continuous steps was used. The only drawback was a slightly longer step in the middle. The participants were asked to take this step with one move.

The study was conducted in accordance with the latest revision of the declaration of Helsinki (Rickham, 1964). All subjects gave their consent before participating in the data collection procedures. The

Table 3: Recording sequence, pauses of 10 - 40 seconds between the activities.

No.	Activity	Time (s)	No.	Activity	Time (s)	No.	Activity	Time (s)
0	walk	20	8	sit	20	16	run	20
1	sit	20	9	walk	20	17	run	20
2	lay	20	10	lay	20	•	•	•
3	stand	20	11	stand	20	•	•	•
4	downstairs	10	12	downstairs	10	•	•	•
5	upstairs	10	13	upstairs	10	•	•	•
6	downstairs	10	14	downstairs	10	•	•	•
7	upstairs	10	15	upstairs	10	•	•	•
							Total	280

data collection was supervised by the authors to ensure the quality of the data.

3.2 Sensor Setup

A *One Plus 6* smartphone (One Plus, China) and *five QuantiMotion IMUs* (Bonsai Systems®, Switzerland) were used for data collection in this study. The smartphone was placed in the *front right pocket* of the subjects, where it might be worn in daily situations. The IMUs have been placed asymmetrically on both body sides covering the *wrist, ankle, upper arm, and upper leg*, the fifth IMU was located at the *lower back*. As seen in Section 2.1.4 regarding best achieving sensor positions in related work, the wrist and thigh provide high classification accuracy for daily life activities. Further sensors were added to the ankle, the arm, and the lower back to cover the rest of the body positions mostly used in other studies.

Based on preliminary experiments, accelerometer and gyroscope data were recorded at 100 Hz and downsampled to *80 Hz*. Several other sampling rates were tested in addition, in order to investigate further the impact of sampling rate on activity recognition accuracy. The acceleration and gyroscope range were $\pm 16\,g$ and $\pm 2000\,°/s$, respectively.

3.3 Recording Tools

A custom Android app was developed for sensor data collection. The app is capable of recording data from the internal sensors in the smartphone as well as multiple external Bluetooth Low Energy (BLE) IMUs. For the current experimental setup, the app provides the subject auditory instructions of the pre-defined recording sequence (e.g., walk, sit, stand), and labels the recorded data with the activities. Using basic text-to-speech components, the subject gets told what happens next, thus can prepare, and start/stop the activity at the right time. This produces clear separated data. It was furthermore ensured that if the Bluetooth connection to the IMUs gets lost, the experiment is paused and resumed at the moment the connection is reestablished.

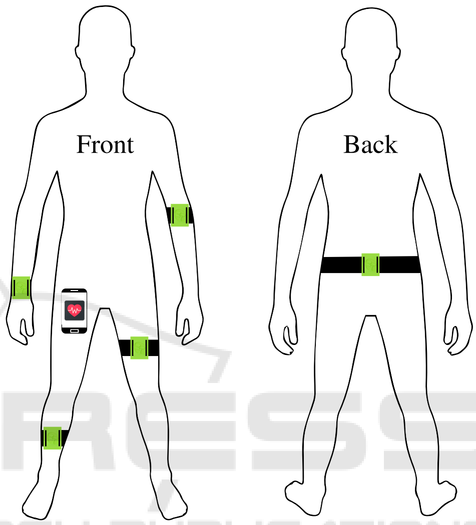


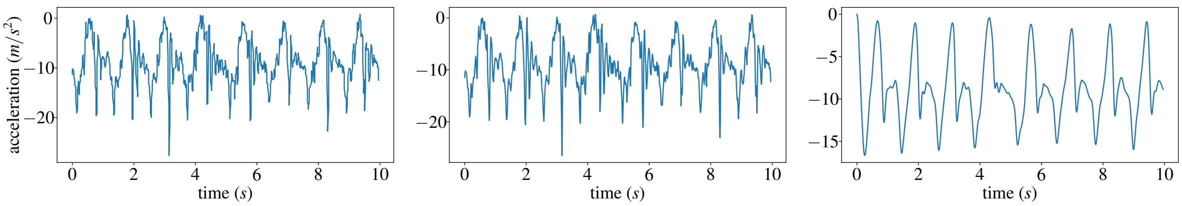
Figure 1: The five Bonsai IMUs were placed on the left thigh, right ankle, left arm, right wrist, and lower back. The smartphone with the recording app (see Section 3.3) was placed in the right pocket.

4 EVALUATION

4.1 Dataset

In this experiment, the data was composed of *18 subjects*. Seven different activities (lay, sit, stand, walk, climb upstairs, climb downstairs, and run) were performed while receiving data from the six used sensors (placing see Figure 1). One subject was not able to climb stairs and run, so only lying, sitting, standing, and walking was recorded. Overall, 720 seconds duration for lying, sitting, standing and walking, and 680 seconds for stair climbing were recorded.

The dataset was split into train, validation, and test



(a) Raw Data (b) Resampled Data (80 Hz) (c) Filtered Data

Figure 2: Preprocessing of acceleration data along the x-axis shown on an example upstairs activity recorded at the left thigh.

data. Different subjects were randomly selected for each of these groups. See Table 4 for the distribution.

Table 4: Subjects' characteristics. *Data is presented as mean ± standard derivation.*

	All	**Train**	**Valid.**	**Test**
Count (f/m)	18 (4/14)	9 (2/7)	3 (1/2)	6 (1/5)
Age	21.89 ± 3.59	22.56 ± 4.92	20.67 ± 0.47	21.5 ± 0.76
Weight (kg)	69.11 ± 7.64	71.22 ± 8.8	66.67 ± 2.36	67.17 ± 6.54
Height (m)	1.77 ± 0.06	1.77 ± 0.05	1.76 ± 0.03	1.77 ± 0.08

4.2 Preprocessing and Segmentation

The raw acceleration and gyroscope data received from the devices were downsampled to the defined sampling rate of 80 Hz and filtered through a Butterworth low-pass filter to remove high-frequency noise. This filter attenuates higher frequency components of the signal beyond a configurable cut-off frequency (Butterworth, 1930). (Wang et al., 2011) proposed for the processing of body sensor networks a 3rd order Butterworth low-pass filter with a cut-off frequency of 4 Hz. The same filter specification has been applied in this experiment. An example sequence of a random subject climbing upstairs and the three preprocessing stages are shown in Figure 2.

In related work, a window length between 0.25 and 0.5 seconds was proposed. Thus, the filtered data was segmented into non-overlapping windows with a size of 0.5 s.

4.3 Classification

Previous works successfully used machine learning methods for HAR (Chen et al., 2020). In two of the latest studies, Convolutional Neural Networks (CNN) were selected as the method achieving the highest recognition precision (Ignatov, 2018; Yang et al., 2015). (Zebin et al., 2016) conducted a very similar experiment to the one in this paper but only using a fixed set of body-worn inertial sensors. They aimed to distinguish between the same activities as in this work except for running. By using a CNN, they reached a recognition accuracy of 97.01%. Thus, a CNN was composed to recognize the activities in this experiment. CNNs are inspired by the biological visual system, they provide a hierarchical feed-forward neural network. A CNN has convolutional layers to learn filters sliding along the input data (Ignatov, 2018) in addition to fully-connected layers of the original neural networks. The convolution and sampling layers work as feature extractors in the ARP (Almaslukh et al., 2018).

The CNNs for this study consist of three convolutional, three pooling, and one fully connected layer. (Ignatov, 2018) for example used 1×16 filters, while in our study, three 1×2 convolution layers separated by pooling layers have been tested to achieve similar results but increase the training velocity. The number of channels depends on the number of IMUs analyzed. Each IMU brings six channels (acceleration and gyroscope in all three axes). For example, if the combination of smartphone and the IMU at the right wrist is investigated, this results in twelve channels (see Figure 3 for the CNN architecture). Based on the amount of sensor combinations tested, there have been trained twelve CNNs. A batch size of 50 and a learning rate of 0.001 were chosen for training the network in 200 epochs.

4.4 Results

The main goal of this work was to determine the impact of different IMU combinations and finding the optimal minimal setup. Thus, single IMU setups and combinations of the smartphone and an additional IMU were investigated. An overview of all possible combinations tested and their results are plotted in Figure 4.

This results show that regarding combinations of the smartphone and an additional IMU, combinations of the smartphone in the *right pocket* and the IMUs at the *right ankle* and the *lower back* provide promis-

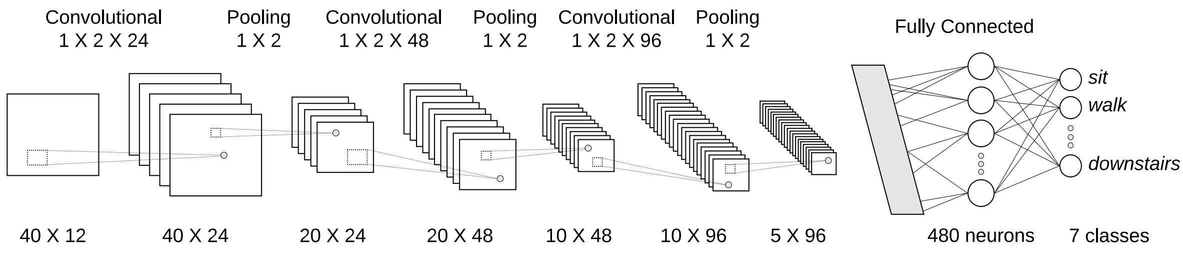


Figure 3: CNN architecture for classification of data from two IMUs.

ing F1-scores of approximately 97% and 96%. As shown in the confusion matrices in Figure 5, the applied classifier had for both most problems recognizing the stairs and walking activities, and for the *right ankle* also with lying while for the *lower back* the prediction of standing was wrong a few more times. Both classified sitting always correct, but sometimes the classifier on the *right ankle* combination confused laying and climbing downstairs as sitting.

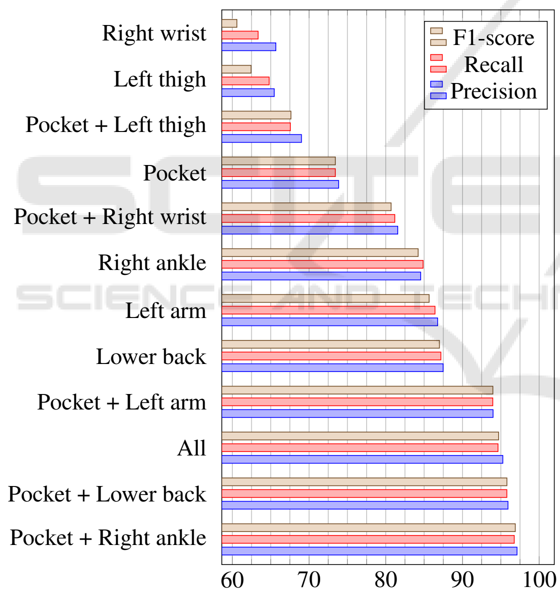


Figure 4: Recognition performance for the different sensor combinations. *Pocket* describes the smartphone in the right pocket.

Furthermore, the combination of the *pocket* and the *left arm* produces a high F1-score of 94%. For this combination, walking and the stairs activities were miss-classified by more than 10%, but the remaining activities were recognized nearly correctly. The other smartphone and IMU combinations have most difficulties recognizing sitting, lying, and walking. Standing, the stair climbing activities and running achieve high performance. They all score lower than 81%.

In comparison to the remaining activities, walking

Actual activity \ Predicted activity	Walk	Sit	Stand	Lay	Upstairs	Downstairs	Run
Walk	95.28	0	0	0	2.36	2.1	0.26
Sit	0	100	0	0	0	0	0
Stand	0	0	99.25	0	0.25	0.5	0
Lay	0	8.27	0	91.73	0	0	0
Upstairs	2	0	0.25	0	94.5	3.25	0
Downstairs	1	0.25	0	0	1.25	97	0.5
Run	0	0	0.25	0	0	0.25	99.5

(a) Pocket and right ankle

Actual activity \ Predicted activity	Walk	Sit	Stand	Lay	Upstairs	Downstairs	Run
Walk	94.49	0	0.26	0	0.26	4.99	0
Sit	0	100	0	0	0	0	0
Stand	0.5	0	93.5	0	0.75	5.25	0
Lay	0	0	0	100	0	0	0
Upstairs	7	0	0	0	90.25	2.25	0.5
Downstairs	4.75	0	0	0	0.25	92.5	2.5
Run	0	0	0	0	0.25	0	99.75

(b) Pocket and lower back

Figure 5: Confusion matrices of IMU combinations with the highest performance.

and the stairs activities were predicted wrong more often. This might be related to the similarity of the three activities. Maybe also the long step in the middle of the stairs caused the subjects to walk similar to normal walking for a short time because they had to make a big step.

Table 5: CNN classification performance of the different single IMUs.

Position	**Precision**	**Recall**	**F1-score**
Right pocket (Smartphone)	73.85%	73.42%	73.43%
Left thigh	65.46%	64.79%	62.44%
Right ankle	84.55%	84.86%	**84.22%**
Left arm	86.76%	86.42%	85.65%
Right wrist	65.67 %	63.36%	60.59%
Lower back	87.48%	87.18%	**87.00%**

Table 6: CNN classification performance from the combinations of the smartphone in the right pocket with another IMU sensor.

Sensor added	**Precision**	**Recall**	**F1-score**
-	73.85%	73.42%	73.43%
Left thigh	69.01%	67.56%	67.64%
Right ankle	97.11%	96.75%	**96.89%**
Left arm	93.99%	93.95%	93.96%
Right wrist	81.56%	81.18%	80.69%
Lower back	95.93%	95.78%	**95.79%**

In Table 5, the results of single sensor setups are presented. Also as such a single sensor setup, the IMUs at the *lower back* and the *right ankle* reach the highest recognition performances with 87% and 84.22%, respectively. The smartphone in the *right pocket* as a single IMU results in a F1-score of 73.43%. The achieved improvements by combining the smartphone with IMUs are shown in Figure 6. Merged with the body-worn standalone IMU devices, gains of up to 23.46% are reached with the best combinations as presented above. The worst combination is the addition of the IMU at the *left thigh* which results in the score to decrease by nearly 6%. This might be caused by both sensors being at similar positions (the smartphone in the right pocket and the IMU at the left upper leg) and them producing redundant information as well as missing upper body details.

With lower sampling rates, the recording IMU devices would consume less energy, however, less information may be preserved. With various window sizes, the classification performance could fluctuate drastically. To test the robustness of the classification results in terms of energy consumption and performance, the impacts of lower sampling rates and other window sizes were analyzed. The dataset was downsampled to different sampling rates, segmented in different window sizes, and fed into the CNN. The sam-

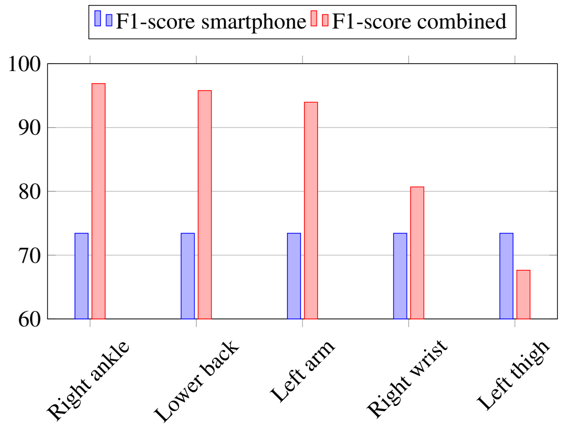


Figure 6: Recognition improvement if the smartphone is combined with each body-worn standalone IMU device.

pling rate appears to make no significant difference regarding the resulting test performance, but a drop of 5% at most can be noticed comparing the results from 80 Hz to those from 10 Hz sampled data. Lower sampling rates still provide sufficient results, but accuracy is significantly lost at frequencies lower than 6 Hz as already investigated by (Klieme et al., 2018). It can be seen that different window sizes also do not make a big change regarding the achieved scores, as long as they do not exceed 2 s and do not fall below 0.25 s. The 0.25–0.5 s that have been proposed by (Banos et al., 2014) also achieve high F1-scores for our dataset, but for this experiment, high recognition performance is also received for windows of 2 s.

The processed data was recorded in a laboratory setting. (Foerster et al., 1999) showed, that an accuracy of 95.6% for ambulation activities performed in controlled data collection environments could be reached. But the accuracy decreased to 66% when instead using naturally recorded data. The high performance of the processed data in this study could hence be strongly related to its controlled generation. Regarding the recorded subjects, it is also essential to notice that apart from the one person mentioned above, those were all participants with unrestricted mobility between 19 and 36 years. Hence the achieved results might be invalid for other groups as for people with health impairments or elderly patients. There have also been some difficulties while recording. BLE in combination with the Bonsai IMUs sometimes caused disconnections and forced the experiment to be re-started. This interruption of the recording protocol might have falsified the results.

5 CONCLUSIONS

Based on an experiment with 18 subjects, it was shown that an additional Bluetooth IMU sensor arrangement can improve the robustness of smartphone-based HAR for daily-life activities. Basic activities can be recognized with a high accuracy depending on the chosen sensor placements. The used CNN reached a high F1-score of 96.89% for a combination of the smartphone in the *pocket* and an IMU on the *right ankle*. Furthermore, combining an IMU on the *lower back* with the smartphone resulted in a score of 95.79% and the combination of the smartphone and the *left upper arm* in a score of 93.96%. Thus, similar results are achieved compared to related work such as the work by (Zebin et al., 2016). They reached 97.01% using five IMUs combined on six basic everyday activities using a CNN. Overall, recognition improvements of up to 23% are possible when combing the smartphone in the pocket with a single IMU sensor at the body compared to when the smartphone was processed exclusively. In addition, it was proven that high sampling rates are not required for the activities in this experiment just as large windows sizes.

A possible future study could (1) discover how the smartphone sensors can be ignored in case the smartphone is not worn in the pocket. One of the primary motivation for the study in this work has been the uncertainty of smartphone positions in the daily life of people. The achieved results could be used to record a dataset with the smartphone on multiple positions where it might be worn with additional IMUs at one (or both) of the identified sensor positions with the best improvement of recognition performance. The goal of the study could then be to always provide a high precision rate by ignoring the smartphone if its placement does provide irrelevant or even misleading information. With the *Body Location Independent Activity Monitoring*, there also already exist approaches trying to solve the problem of different sensor positions with promising results (Figueira et al., 2016).

To consider the obtained results as valid, (2) further activities (such as bicycling) should be investigated. The conducted activities in this study involved either no or a lot of movements in the lower body. That could explain the high performance of the ankle position. Maybe other activities with predominant movements in the upper body can be recognized better using for example the *wrist* position. Also, (3) more subjects from other groups (such as elderly or people with restricted mobility) should be added to the dataset.

The current study only investigated one classifier with a set of optimized hyperparameters. Despite the high performance of the current model, it would be worthwhile to (4) explore effects of different classifiers and more extensive hyperparameter tuning.

The aim of this work was to test different sensor placements, but for more intuitive usability (5) a real-time activity recognition as e.g. in (Andreu et al., 2011) would be an important step to make real use out of HAR for medical problems.

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