A benchmark dataset to evaluate sensor displacement in activity recognition

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ABSTRACT
This work introduces an open benchmark dataset to investigate inertial sensor displacement effects in activity recognition. While sensor position displacements such as rotations and translations have been recognised as a key limitation for the deployment of wearable systems, a realistic dataset is lacking. We introduce a concept of gradual sensor displacement conditions, including ideal, self-placement of a user, and mutual displacement deployments. These conditions were analysed in the dataset considering 33 fitness activities, recorded using 9 inertial sensor units from 17 participants. Our statistical analysis of acceleration features quantified relative effects of the displacement conditions. We expect that the dataset can be used to benchmark and compare recognition algorithms in the future.

Author Keywords
Sensor displacement, Benchmark dataset, Activity Recognition, Motion sensors, Fitness exercises.

ACM Classification Keywords
H.5.2 Information interfaces and presentation (e.g., HCI): Miscellaneous.

General Terms
Experimentation, Human Factors, Measurement, Performance.

INTRODUCTION
Human activity recognition using inertial sensors can extend services and functionalities in many application areas, e.g. in the manufacturing industry [15], sport assistance [5] and user-computer interaction [11]. While wearable sensor systems based on inertial sensors have clear benefits in these applications, sensor measurement anomalies (such as displacement) are key limitations that constrain their wide-spread use. To implement activity recognition, current systems often require that sensors must be attached at predefined positions to discriminate between different actions [2, 13]. Pattern models are derived in a training step before the system's deployment, where the sensor positions are considered to be constant. In particular, for inertial sensors that provide acceleration and orientation measures a constant position at the body cannot be maintained in a real-life deployment. As a consequence, previously trained pattern models may fail to identify actions in the observed sensor data.

Frequently inertial sensors are affected by static and dynamic sensor position changes (displacements) at the user's body. Displacements of inertial sensors could be described through two kinetic transformations: rotations (angular displacements) and translations (linear displacements). Position changes can remain static across the execution of many activity instances, e.g. when sensors are attached with a displacement each day. Dynamic position changes include the effect of loose fitting of the sensors, e.g. when attached to cloths [9]. The effect of attachment-related changes on sensor measurements is profound, as sensor data distributions can change widely and across extended time spans compared to expected patterns. To date, some investigations have aimed to quantify and attempted to combat displacement effects in inertial sensors. However, there is no consensus on the methods to use (see Section Related Work for more detail). Neither are there adequate benchmark datasets available that can be considered for comparing approaches that deal with sensor displacements.

This work presents a novel dataset that can be considered to approximate realistic performance of activity recognition methods in dealing with displacement effects. For this purpose, we introduce a concept of gradual sensor displacement conditions that were subsequently analysed in our benchmark dataset. [1] In particular, this paper provides the following contributions:

- We introduce a concept of gradual displacement in inertial sensors, considering ideal, user self-placed, and mutually

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[1]The benchmark dataset and the activity annotations can be found at `http://www.actlab.ele.tue.nl/datasets`.

displaced conditions. Here, ideal and mutually displaced conditions may represent performance bounds of activity recognition systems. The self-placed condition reflects realistic sensor data variance due to displacement introduced by users rather than system developers attaching the sensors.

- We report on the protocol and acquisition of the benchmark dataset to investigate sensor displacement in inertial sensors, considering acceleration, gyroscope and magnetic field modalities in three dimensions. In total, 9 on-body sensors were used with 17 study participants performing 33 fitness activities.

- We present a statistical analysis of the sensor displacement effects, including the data distribution shifts observed for the displacement conditions considered.

In this work, we specifically focus on mean and standard deviation features only to minimize assumptions regarding adequate feature extraction and selection. This allows us to provide a baseline description of the effect that self-placement and mutual-displacement conditions introduce, compared to ideal sensor placements. We consider this step as essential to enable follow-up investigations aiming at analysing and comparing recognition techniques based on this new benchmark dataset.

RELATED WORK

Recognition approaches robust to sensor displacement

Sensor displacement is a well known problem in activity recognition. Several approaches have been proposed in literature to increase the robustness of recognition methods to sensor displacements. One main direction is to identify displacement invariant features for recognition. Kunze et al. [12] studied how acceleration and gyroscope signals are affected by sensor displacement. They distinguished between gravitational, translational, and rotational components in the acceleration signal and showed that only the acceleration component due to rotation is sensitive to sensor displacement. Based on this observation they proposed a heuristic method which achieved higher recognition rates for within a body part sensor displacement. Another approach that uses displacement invariant features was proposed by Foerster et al. [7]. By extracting signals from several locations within a body segment and applying a genetic algorithm for feature selection they identified features invariant to sensor displacement. They validated their approach using a HCI and a fitness dataset (see next subsection) and achieved improved recognition results with respect to standard features.

Another main direction to increasing recognition robustness against sensor displacement is adapting the classifiers to the resulting shifts in the feature distribution. Bayati et al. [3] proposed an unsupervised adaptation method based on the EM algorithm. They assumed that the anomalies introduced by sensor displacement can be charaterized as a covariate shift [16]. They estimated this shift using an online version of the EM algorithm and transformed the incoming samples back in the feature space before classification. They tested their method on HCI, fitness and daily living scenarios. While the previous method applied a transformation in the feature space, Foerster et al. [8] proposed an online self-calibration method to adapt the classifier model. The method consists of a calibration phase and a recognition phase. The calibration phase is triggered by the user when he observes that the recognition accuracy drops. In this phase the cluster centers of the nearest centroid classifier are adjusted at a predefined learning rate using the incoming instances after classification. The process is stopped when the gradient of the distance between the adapted class center and the original class center drops below a certain threshold.

The works cited above indicate that the problem of sensor displacement is well acknowledged and has attracted significant research attention from the activity recognition community. Ideally, the proposed methods could be compared on a dataset that is sufficiently large and considers various aspects of sensor displacement.

Datasets for activity recognition

Several activity recognition datasets are available that target different aspects of the activity recognition problem. Bao and Intille [2] were one of the first to introduce the concept of activity recognition under naturalistic conditions. They collected a dataset of 20 participants wearing 5 on-body biaxial accelerometers and performing 20 activities with no supervision or detailed instruction. This idea was later incorporated to a broader extent in the PlaceLab [10], a live-in laboratory for the study of ubiquitous technologies in home settings. Volunteers individually participated living in this lab for several days or weeks, and being recorded by devices integrated into the fabric of the PlaceLab architecture. The lack of activity recognition data that support the research on opportunistic sensor configurations inspired the OPPORTUNITY dataset [14]. This multimodal sensor and content rich database contains over 25 hours of sensor data for 12 participants stemming from 72 sensors with 10 modalities. The dataset was collected in a room equipped with a kitchen where the subjects performed morning activities in a naturalistic way. Multimodal data collection have been also explored for activity-specific tasks of different granularity. The Carnegie Mellon University Multimodal Activity database (CMU-MMAC) [6] contains multimodal measures of the human activity of subjects performing the tasks involved in cooking and food preparation. Different sensor modalities were considered in this study to capture the user motion as audio, video, IMU or RFID among others. Anomalous situations were also introduced in order to analyze the effect on subject behavior when performing regular activities.

The BodyAttack fitness dataset and the HCI gestures dataset collected at ETH Zurich both explicitly target sensor displacement related anomalies. In the fitness dataset 6 activity classes are considered with 10 accelerometers mounted on one leg. In the HCI dataset 5 gestures are executed in a vertical plane with 8 accelerometers mounted on the arm. Both datasets contain data for a single participant. As the dataset focus on translational displacement, the sensors were mounted with roughly the same orientation to minimize rotational variation. These datasets have been used to validate some of the methods mentioned in the previous section. The OPPORTUNITY dataset has been also used to validate the robustness of the method in [4] against sensor rotation, however since sensor rotations are not part of the original dataset they were introduced synthetically. These datasets are generally constrained in terms of targeted body parts, number of subjects, number of activities and even the displacement considered since they focus exclusively on translation. Moreover, they usually lack a realistic user-self-placement mode of introducing sensor displacement and rely solely on a mutual or induced displacement. Thus, a dataset that integrates ideal-placement, self-placement and mutual-displacement concepts is required for testing sensor displacement detection and recovery techniques.

CONCEPT OF SENSOR DISPLACEMENT

Sensor measurement anomalies could be categorized in issues related to (1) sensor hardware and (2) sensor displacement. Examples of technical anomalies include bias, scale factors, nonlinearity and electronic noise among others, normally due to decalibration or battery failure. Some effects of sensor anomalies are shown in Figure 1. This work focuses on displacement related sensor anomalies. This anomaly is highly relevant in inertial sensors, which are extensively used in activity recognition applications.

Sensor displacement leads to a new sensor position which results in a change in the signal space. However, the impact of displacement on the sensor signal may vary depending on several factors. The magnitude of the displacement as well as the body part considered determine the degree to which the measurement is affected. Thus for example, a sensor which is displaced from the upper arm to the lower arm will generally measure higher accelerations. While these displacements of sensors between different limbs may be less probable in real-life applications, shifts and rotations on the same limb occur frequently. These displacement effects are also subject to the particular activities, gestures or

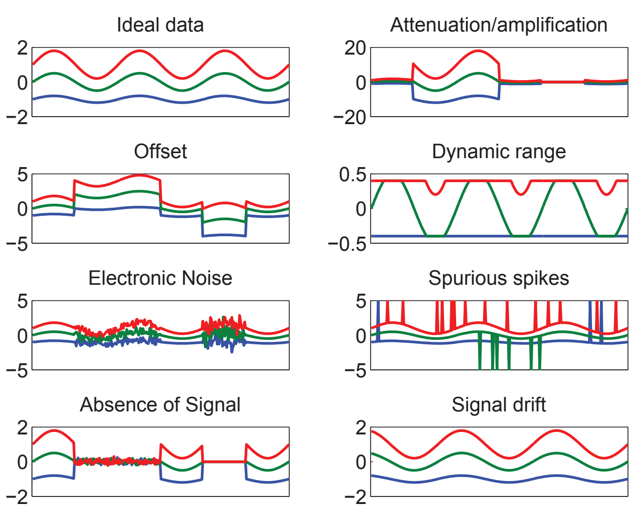


Figure 1. Synthetic examples of modelable technological anomalies.

movements the user performs. Moreover displacements affect each sensor modality differently. Acceleration is especially sensitive to rotations, because it causes a shift in the direction of the gravitational component in the sensor reference frame. Gyroscopes or rate of turn sensors are robust to rotations along their rotation axis and to translations along the same body limb. The compass (magnetic field sensor) measurement is affected by rotations and to a lower extent by translations when assuming no gimbal lock degeneration.

SENSOR DISPLACEMENT

A predefined sensor deployment is frequently considered for activity recognition tasks. The recognition system is usually trained on this ideal setup. However, users may introduce sensor displacement as consequence of the self-placement of the sensors or during the performance of the exercises which might lead to misclassification of the activities and an overall lower performance of the recognition system. In this work we propose a means of introducing sensor displacement anomalies in a practical and structured fashion and study their effect in the benchmark dataset. We aim to evaluate the variability introduced by sensors self-positioning with respect to an ideal setup as well as investigate the effects of large sensor displacements. In order to do so we define the following three scenarios regarding the sensor deployment:

1. *Ideal-placement* or *default* scenario. The sensors are positioned by the instructor to predefined locations within each body part. The data stemming from this scenario could be considered as the 'training set' for supervised activity recognition systems.

2. *Self-placement*. The user is asked to position a subset of the sensors themselves on the body part specified by the instructor. This scenario tries to simulate some of the variability that may occur in the day to day usage of an activity recognition system, involving wearable or self-attached sensors. Normally the self-placement will lead to on-body sensor setups that differ with respect to the ideal-placement. Nevertheless, this difference may be minimal if the subject places the sensor close to the ideal position.

3. *Mutual-displacement*. An intentional de-positioning of sensors using rotations and translations with respect to the ideal placement is introduced by the instructor. One of the key interests of including this last scenario is to investigate how the performance of a certain method degrades as the system drifts far from the initial setup.

DATASET DESCRIPTION

Activity set

The dataset consists of a set of typical warm up, fitness and cool down exercises (see Table 2). In particular we included, activities involving translation (L1-L3), jumps (L5-L8) or general fitness exercises (L31-33) as well as body part specific activities focused on the trunk (L9-L18), upper extremities (L19-L25) and lower extremities (L26-L29). Some activities imply the motion of the whole body (e.g., walking or jumping) while others focus on training individual parts

(a) (b) (c)

Figure 2. Example of possible sensor placements according to the (a) ideal (b) self-placement and (c) mutual-displacement deployments. In (b) the sensor is arbitrarily rotated 180° (approx.) by the user with respect to the ideal positioning (a). In (c) the expert explicitly displaces the sensor from the middle upper arm to the elbow.

Type of displacement	Description
Ideal-placement	No displacement is introduced. This is the default sensor deployment
Self-placement	The users are asked to position a subset of the sensors by themselves on the specified body part/s (i.e., "please position sensor *X* on your left thigh")
Mutual-displacement	Sensors are intentionally displaced from the ideal position by the system developpers, typically introducing a large displacement

Table 1. Methods for implementing sensor displacement.

(e.g., legs for cycling). Since the activities were very easy to perform, participants had no difficulty in doing the exercises. The activities were selected so that different combinations of body parts are involved in each exercise. The type of exercise also affects the impact of the displacement on the sensor signals. Rotation related anomalies will be constantly present, even when the sensor is not in motion, due to the different orientation of gravity in the sensor frame. On the other hand translation related anomalies might only be observable when the sensor is in motion.

Study setup

A set of 9 inertial measurement units (Xsens [17]) are distributed on the subject's body as shown in Figure 3. These nodes provide several sensing modalities including acceleration, rate of turn, magnetic field and derive the orientation estimates of the sensor frame with respect to the Earth reference. The sensors and the Xsens master are wired together in a serial connection. The Master device is interfaced over Bluetooth to a laptop which continuously stores the information delivered by the nodes. The laptop is also used for labeling purposes. Both the data storage and the labeling process are performed using the CRN Toolbox [1]. The sampling rate is established to 50Hz which suffices the exercises

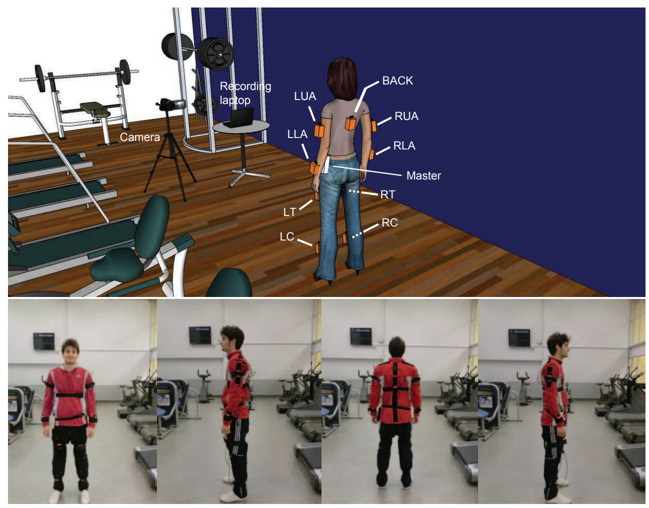


Figure 3. Experimental setup (cardio-fitness room). Eight Xsens units are placed on each body limb and an additional one on the back. A laptop is used to store the recorded data and for labeling tasks. A camera records each session for offline post-processing.

requirements.

Eight of the sensors are normally positioned on the middle of the limb (for each extremity). An additional one is centered on the back, slightly below the scapulae. The sensors were tightly attached to the body using elastic straps and velcro. Trousers and sports jackets of different sizes were provided in order to ensure the fit to the user.

All sessions were recoded using a video camera. The video recording is useful to check anomalous or unexpected patterns in the data and correct labeling mistakes. In some recordings two subjects performed the exercises in parallel for efficiency.

Experimental protocol

The experiments took place in a cardio-fitness room. The experiment consisted in performing two complete runs of the

Activity set		
L1: Walking (1 min)	L12: Waist rotation (20x)	L23: Shoulders high amplitude rotation (20x)
L2: Jogging (1 min)	L13: Waist bends (reach foot with opposite hand) (20x)	L24: Shoulders low amplitude rotation (20x)
L3: Running (1 min)	L14: Reach heels backwards (20x)	L25: Arms inner rotation (20x)
L4: Jump up (20x)	L15: Lateral bend (10x to the left + 10x to the right)	L26: Knees (alternatively) to the breast (20x)
L5: Jump front & back (20x)	L16: Lateral bend arm up (10x to the left + 10x to the right)	L27: Heels (alternatively) to the backside (20x)
L6: Jump sideways (20x)	L17: Repetitive forward stretching (20x)	L28: Knees bending (crouching) (20x)
L7: Jump leg/arms open/closed (20x)	L18: Upper trunk and lower body opposite twist (20x)	L29: Knees (alternatively) bend forward (20x)
L8: Jump rope (20x)	L19: Arms lateral elevation (20x)	L30: Rotation on the knees (20x)
L9: Trunk twist (arms outstretched) (20x)	L20: Arms frontal elevation (20x)	L31: Rowing (1 min)
L10: Trunk twist (elbows bended) (20x)	L21: Frontal hand claps (20x)	L32: Elliptic bike (1 min)
L11: Waist bends forward (20x)	L22: Arms frontal crossing (20x)	L33: Cycling (1 min)

Table 2. Warm up, cool down and fitness exercises considered for the activity set. In brackets the number of repetitions (Nx) or duration of the exercises (in minutes).

exercices, once with the self-placed and once with the default sensor setup. The self-placed run was perfomed first as to not give any clues on the defaut sensor position to the participant. One run-through of the exercises lasted 15-20 minutes. Each session was preceeded by a preparation phase lasting around 30 minutes. The preparation phase consisted in positioning the sensors on the subject, connecting the sensors to the XBUS Master, setting up the video camera, and establishing the bluetooth connection between the XBUS Master and the laptop. Before starting the exercises we documented the exact position of the sensors using the video recording. An instructor demonstrated each exercise before the user performed them. In general 20 repetitions are recorded for each activity except for those exercises that required the subject's interaction with gym machines (i.e., L1-L3 and L31-L33 from Table 2) for which roughly a minute of exercising was recorded. This constitutes an interesting means of gaining a relevant number of instances for each class. The two runs were separated by a break during which we checked the battery levels and prepared the setup for the next run. The exercises were labeled online using the CRN toolbox [1]. The inevitable errors in the online labeling were eliminated in post processing with the help of a commentary sheet to track the errors in addition to the video recording.

DATASET EVALUATION

Statistics

In Table 3 we present the statistics on the available exercise data with respect to the complete recorded data for each displacement concept considered in this work. The entire dataset contains over 10 hours of exercise data and lasts over 39 hours in total. Self-placed and ideal recording sessions contain approximately 15 hours of data each. Mutual-displacement sessions include more then 10 hours of data distributed on the different runs. The difference between exercise duration and the total duration provides the amount of data corresponding to unrelated activities. The average $\pm$ standard deviation duration in minutes of the exercise data (total data) recorded per subject is 13.02 ± 5.26 (51.31 ± 20.35) for the ideal case, 13.96 ± 3.78 (50.59 ± 17.41) for the self-placement and 14.75 ± 5.36 (49.24 ± 22.43) for the induced concept.

During the data post-analysis some parts of the recordings were identified as either corrupted or missing. The recorded videos were demonstrated especially useful for rejecting erroneous labels as well as checking the validity of the annotated data. Figure 4 show the missing activity data for each subject or run. No activity data is available for subject 6 and 13 for the self-placement setup. For participant 7 there is almost no data available in the ideal scenario. A few additional activities are missing for some of the remaining subjects. For the mutual-displacement dataset (Figure 4(b)), the worst data loss was incurred for subject 3 where activities L13 to L29 are missing. A few additional activities are also missing for the rest subjects. Finally, the sensors that have been displaced for each subject and setup are depicted in Figure 5.

Analysis of sensor displacement effects

We have conducted a preliminary analysis of the variability captured in this dataset to underline that it is indeed useful for studying displacement related sensor anomalies and can be considered for benchmarking displacement invariant features and adaptive techniques. Mean and standard deviation features are considered for acceleration signals across all sensors. The data is partitionned in such a way that each instance corresponds to roughly one repetition of a given activity. Figure 6 gives a particular example of how the feature distribution is affected by sensor displacement. We can observe the shift in the feature space for the displaced sensor between the ideal and self-placement scenario. Figure 7 shows the variance along the principal components of the features across all subjects for each activity performed for the self-placement and the default scenario. In the ideal sensor placement the variance observed is due to the intra and inter subject variability in performing the exercises. The random sensor displacements introduced in the self-placement

Deployment	#subjects	#anomalous sensors	#activities duration/total duration
Ideal-placement	17	0	226.84/860.19
Self-placement	17	3	220.73/895.42
Mutual-displacement	3	{4,5,6,7}	{47.72,45.39,48.58,46.76}/632.28

Table 3. Dataset description summary. Overall cumulative duration for the complete set of activities with respect all the data is given in minutes.

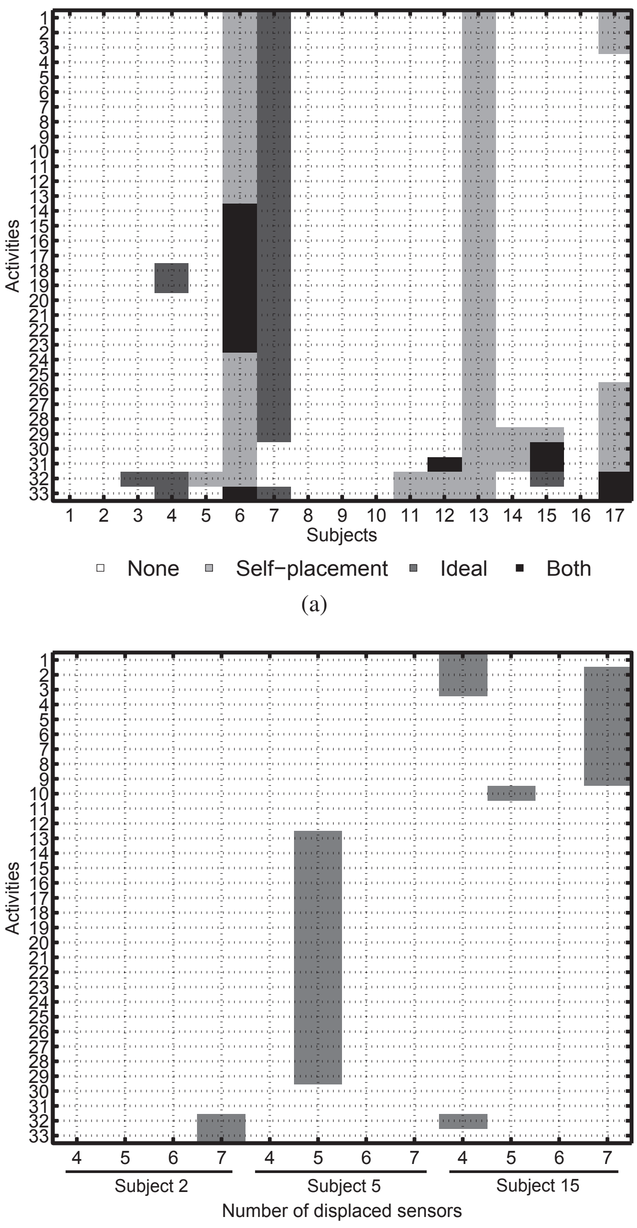


Figure 4. Missing activity data for each particular subject. (a) For ideal and self-placement conditions: the legend identifies the corresponding sensor deployment (*both* ≡ self-placed and ideally-placed). (b) For the mutual-displaced condition: only participants 2, 5 and 15 were considered.

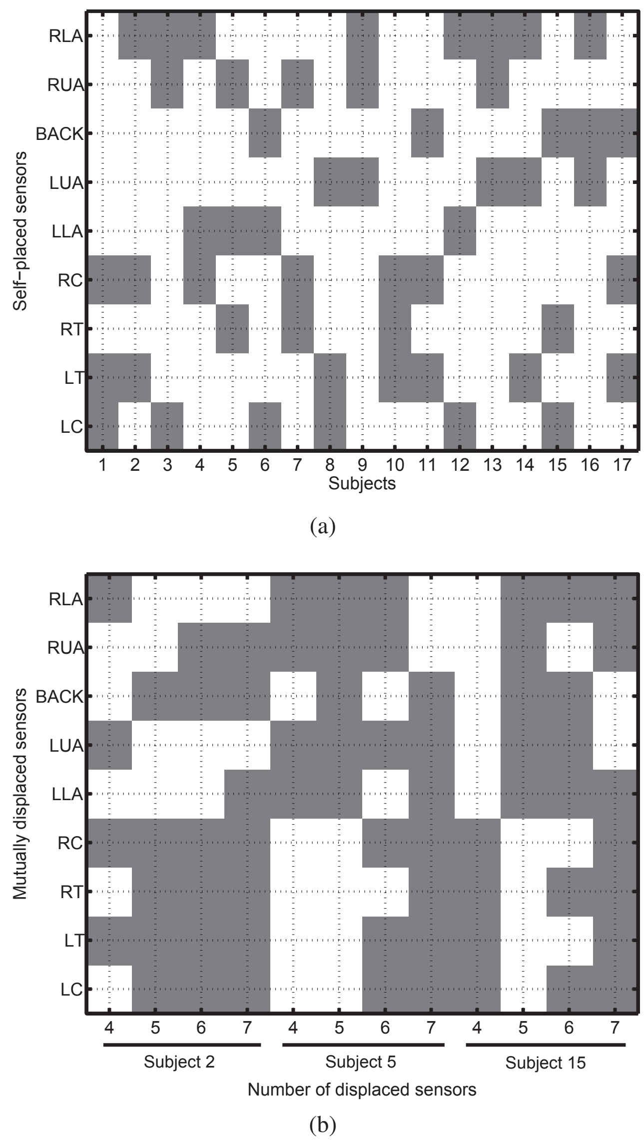


Figure 5. Shading spots identify the displaced sensors for the a) self-placement and b) mutual-displacement deployments. Only participants 2, 5 and 15 were considered in b).

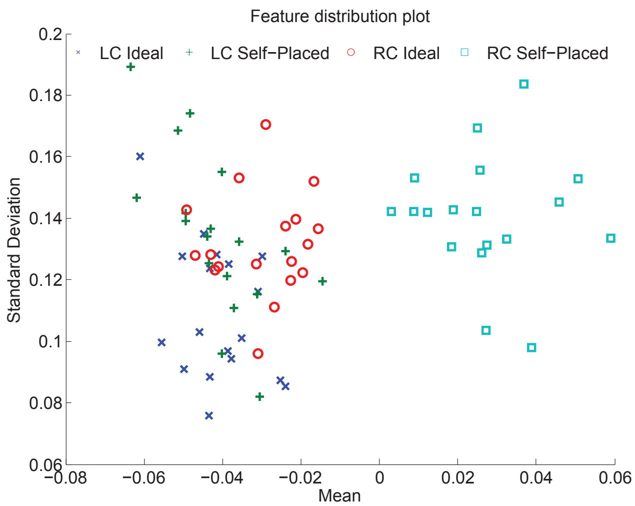


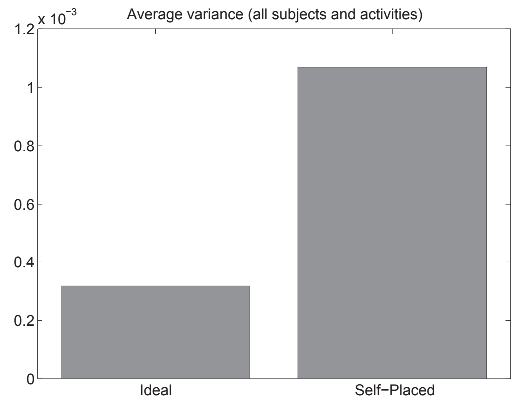
Figure 6. Example of the data drift introduced by the sensor self-placement. The sensor attached to the right calf (RC) was one of the sensors positioned by the user during the self-placement recording session while the left calf (LC) was placed in the ideal position. A shift in the data distribution may be observed between ideal and self-placement run for the displaced sensor, while that of the non-displaced sensor stays the same.

scenario result in a higher overall variance, which can be seen by comparing Figure 7(a) to Figure 7(b). By marginalizing over the activities and feature dimensions we obtain an indicator of average variance for each scenario shown in Figure 9. Figure 9(a) compares the average variance for the ideal and self-placement setup. Even though the users only displaced 3 out of 9 sensors within the specified body segment in the self-placement scenario, the increase in variance compared to the ideal setup is considerable. This result suggests that activity recognition systems that do not consider sensor displacement mask a huge source of variability. Figures 8(a) to 8(f) provide a similar illustration for the mutual-displacement runs.

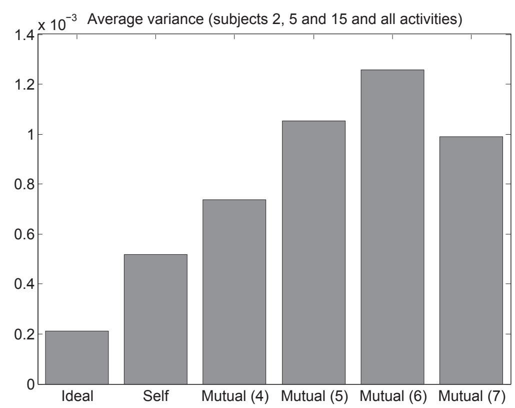
We can consider that the exercises instances for a given participant form a cluster in the feature space (Figure 6). By calculating the normalized cluster distance for a given subject and activity between the ideal and an anomalous setup we obtain the shift in the feature space caused by the sensor displacement. Figure 10 shows the normalized cluster distance between the ideal and self-placement run for subject 10. The feature directions with the highest cluster distances indicate the three particular sensors (LT, RT and RC, see Figure 5) the participant displaced.

Classification impact of sensor displacement

Even though it is not a primary goal of this work to propose a method for dealing with sensor displacement, we conducted a brief classification study to demonstrate the sensor displacement effect in the activity recognition process. Three well-known classification techniques - nearest class center (NCC), k-nearest neighbors (KNN) and decision trees (DT) - were considered to evaluate the recognition performance in the ideal, self-placement and mutual-displacement (seven



(a)



(b)

Figure 9. Variance across subjects averaged over activities and features. In (b) the ideal and self-placement results are obtained from the data of participants 2, 5 and 15. For the mutual-displacement the number of de-positioned sensors is given in brackets.

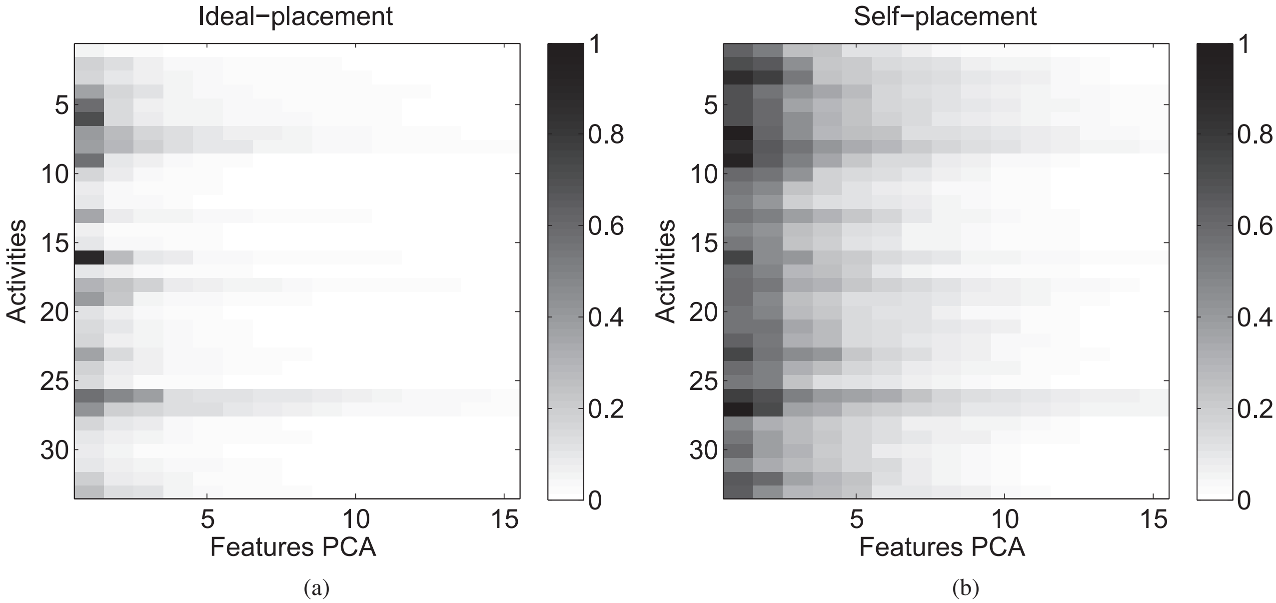


Figure 7. Normalized variance across participants for each activity along the 15 most significant principal components for the ideal and self-placement scenarios. The components are evaluated over the mean and standard deviation features extracted from the tri-axial accelerometer measurements for the 9 sensors.

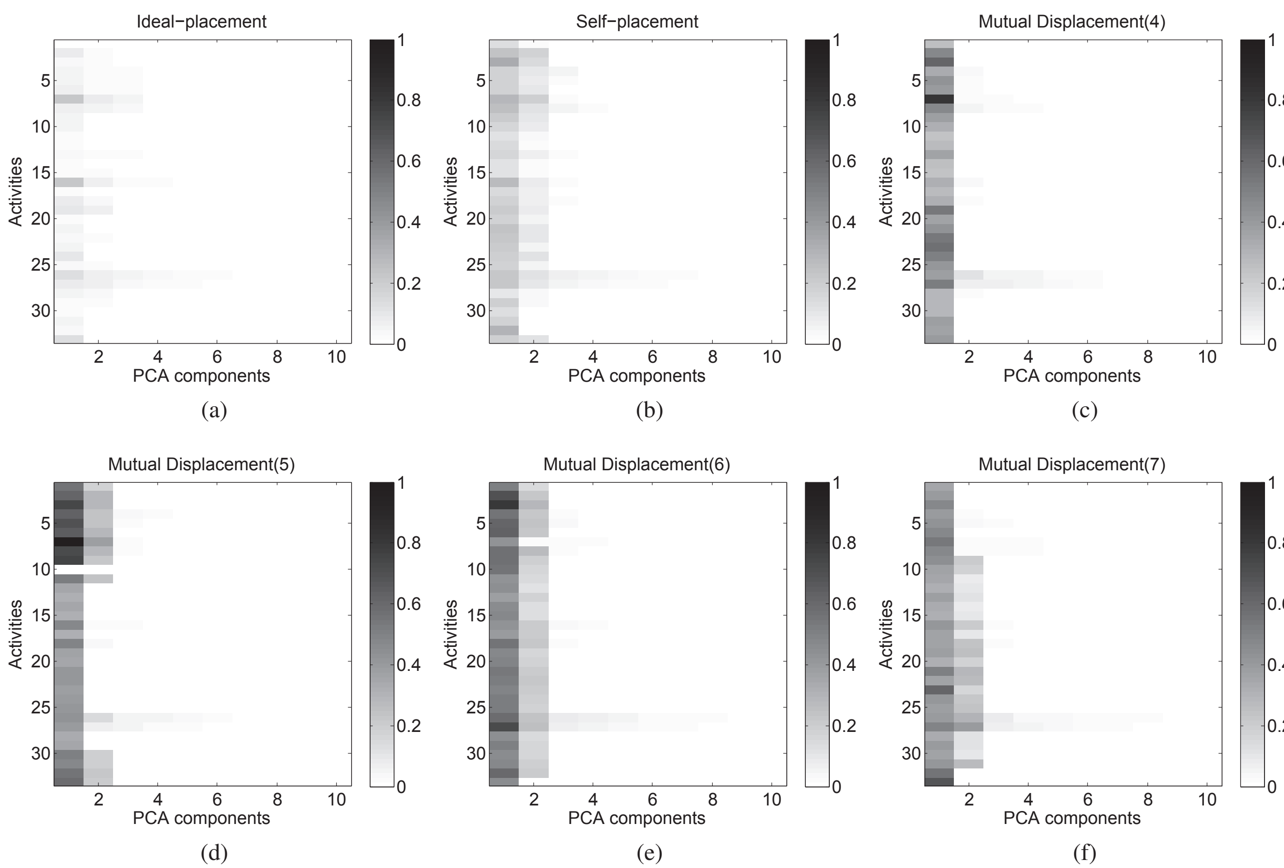
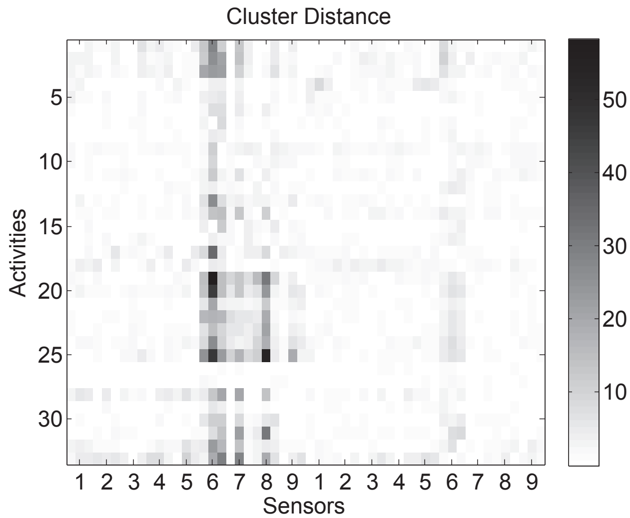
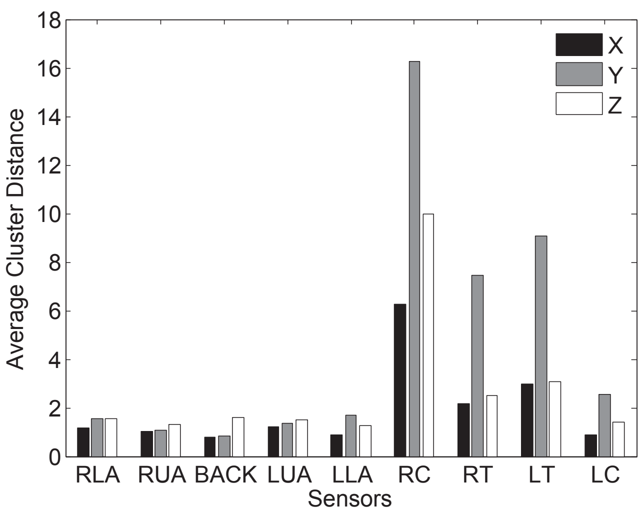


Figure 8. Normalized variance across participants for each activity along the 10 most significant principal components for the mutual-displacement subset. The components are assesed over the mean and standard deviation features extracted from the tri-axial accelerometer measurements for the 9 sensors.



(a)



(b)

Figure 10. Example of the cluster distances between activities for ideal and self-placement recordings for participant 10. Sensors RC, RT and LT were self-placed. Clusters were obtained from mean and standard deviation features along the X Y Z axes of the acceleration measurement of each sensor (in (a) 1 to 9 ≡ *RLA, RUA, BACK, LUA, LLA, RC, RT, LT, LC*) for all annotated dataset activities. In (b) only the mean is considered along the same directions.

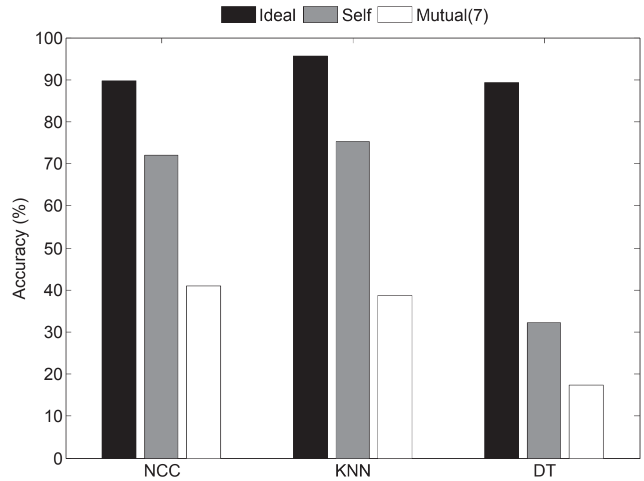


Figure 11. Classification accuracy results for the ideal, self-placement and mutual-displacement scenearios. The ideal-placement scenario was 5-fold cross validated, while the self-placement and mutual-displacement scenarios were tested on a system trained from ideal-placement data. Those runs with seven displaced sensors were considered for the mutual-displacement evaluation. Legend: NCC ≡ nearest class center, KNN ≡ k-nearest neighbor, DT ≡ decision trees.

de-positioned sensors) scenarios. For the ideal case, a 5-fold random-partitioning cross validation process was applied across all subjects and activities. This process was repeated 100 times. A testing procedure was applied for the other two scenearios. Thus, the data collected from the self-placement and mutual-displacement scenarios were tested on a classifier trained across all data from the ideal-placement recordings. For the sake of simplicity the mutual-displacements runs that correspond to the de-positioning of seven out of the nine sensors were considered. Similar features to the ones used for the previous statistical analysis (i.e., mean and standard deviation for acceleration signals across all sensors) were here considered and computed over a non-overlapping sliding window (the size of the window was fixed to 6 seconds).

Figure 11 depicts the results for the above described experiments. The recognition accuracy for the self-placement case drops around 20% for the NCC and the KNN classifiers, and more than 50% when the DT is used with respect to the ideal case. The impact is remarkably higher when seven sensors are displaced for the mutual-displacement scenario. These examples demonstrate the sensor displacement effect on the recognition system capabilites after the sensor deployment is varied with respect to the default setup.

CONCLUSIONS AND FURTHER WORK

We introduced in this work a concept for categorising inertial sensor displacement conditions in ideal, self-placement, and mutual-displacement. The ideal and mutual-displacement conditions represent extreme displacement variants and thus could represent boundary conditions for recognition algorithms. In contrast, self-placement is reflecting a users perception of how sensors could be attached, e.g. in a sports or lifestyle application. The dataset may thus become a valuable tool to compare performance of different methods and conditions.

With the large set of annotated activities, the dataset will lend itself primarily for activity classification problems. A wide variety of sensors were considered for displacements to capture potential effects on a recognition methods' feature extraction and recognition.

Our analysis of the displacement effects confirmed that mean shifts and increased variance can be observed from ideal to self-placement condition. This result was further confirmed by PCA analysis of all acceleration sensors across the activities. Moreover, the cluster analysis confirmed substantial distance increases between ideal and self-placement conditions can be obtained. These distances would subsequently affect simple activity classification methods, such as a nearest centroid algorithm.

We expect that in further works that will consider the new benchmark dataset provided, the effect of displacement can be investigated and recognition algorithms compared.

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