Handling Displacement Effects in On-Body Sensor-Based Activity Recognition

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Abstract. So far little attention has been paid to activity recognition
systems limitations during out-of-lab daily usage. Sensor displacement
is one of these major issues, particularly deleterious for inertial on-body
sensing. The effect of the displacement normally translates into a drift
on the signal space that further propagates to the feature level, thus
modifying the expected behavior of the predefined recognition systems.
On the use of several sensors and diverse motion-sensing modalities, in
this paper we compare two fusion methods to evaluate the importance
of decoupling the combination process at feature and classification lev-
els under realistic sensor configurations. In particular a 'feature fusion'
and a 'multi-sensor hierarchical-classifier' are considered. The results re-
veal that the aggregation of sensor-based decisions may overcome the
difficulties introduced by the displacement and confirm the gyroscope as
possibly the most displacement-robust sensor modality.

Keywords: Sensor displacement, Sensor network, Sensor fusion, Activ-
ity recognition, Human Behavior, Motion sensors.

1 Introduction

The development of systems and mechanisms capable of analyzing the human
behavior has attracted tremendous attention during the last few years. The
potential of activity recognition (AR) applications supports such interest and
evidences their wide possibilities. Monitoring and identifying people routines or
actions may be used in domestic contexts to avoid or alert from risk situations
such as falls or faintings or promote healthier lifestyles through personalized
guidelines and recommendations [1]. Workplace environments may also leverage
the use of AR systems to increase for example the productivity in industrial
maintenance or reinforce safety procedures [14]. Field-specific systems may also
help high-level athletes to improve their performance or scores as well as am-
ateurs to get insights about how to make faster progresses within a particular
sport discipline [11].

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Although there are hundreds of contributions that tackle the activity recognition problem, the maturity of this field is still reduced due to numerous unresolved issues related to systems reliability, robustness, pervasiveness and seamless of usage. One of these unresolved matters is sensor displacement, which is particularly critical in on-body inertial-sensing. Body sensors are usually located in specific places recommended by the manufacturer, however their use under daily living circumstances demonstrate that wrong attachments, loss of fitting or abrupt movements frequently drive to sensors de-positioning. Only a few contributions have analyzed issues in this regard. Kunze *et al.* described a first attempt to self-characterize sensors' on-body placement [9] and orientation [10] from the acceleration analysis during walking. They also demonstrated the effect of rotations and displacement in accelerometers, and proposed a way to partially deal with them through the use of additional sensor modalities [8]. These heuristic methods are coupled to the assumption that the user performs the specific activities required at some point, which nevertheless might not always be guaranteed. Foerster *et al.* [7] studied the possibility of systems self-calibration through the adjustment of the classifier decision boundaries. This supports tracking the changes experimented in the feature space due to the sensor displacement. Similarly in [5] the authors proposed a method to compensate the data distribution shift caused by sensor displacements through the use of an expectation-maximization algorithm and covariance shift analysis.

As an alternative, sensor fusion may be encountered to cope with displacement effects. A key advantage is that identifying the failure sources is not necessarily required to compensate the associated errors in the activity recognition process. Just a few previous works addressed this problem in this regard. Zappi *et al.* [15] showed a significant tolerance increase by using a large set of sensors in combination with majority voting or naive Bayes decision fusion models. A more sophisticated scheme is presented in [13] which attempts to detect anomalies and potential affected sensors in order to remove them from the sensor ecology. Similarly, in [3] the authors applied sensor fusion for dealing with synthetically induced sensor anomalies.

In this work we apply two fusion models that are ultimately compared in terms of accuracy and robustness. The models are tested on a realistic dataset especially intended to benchmark techniques that deal with the effects of sensor displacement and de-positioning in activity recognition. The rest of the paper is organized as follows. In Section 2 the effects of displacement on inertial monitoring are described. Section 3 briefly introduces the AR methodology while Section 4 presents the experimental setup. Results and discussion are provided in Section 5. Finally, Section 6 summarizes main conclusions.

2   Sensor Displacement Effects

The concept of sensor displacement (in application to inertial on-body sensing) may be understood as the combination of two transformations: rotations and translations. According to the physics of the rigid body, rotations refer to the

circular movements that the sensor experiences around its rotation axes or upon itself. Translations correspond to the movements of the sensor from a given position to another distant position through a specific direction.

Sensor displacement applies to each inertial sensing modality (acceleration, rate of turn, magnetic field) to a different extent. Thus for example, acceleration is especially sensitive to rotations. Rotations determine a change in the sensor local frame of reference with respect to its original spatial distribution. This causes a shift in the direction of the gravitational component with respect to the sensor reference frame. The effect of translations is normally more dependent on the initial and end position as well as the magnitude of the acceleration experienced by the sensor. More robust to displacement anomalies are gyroscopes, which are minimally affected by rotations along their rotation axis and translations along the same body limb. Magnetic field measurements are also affected by rotations and to a lower extent by translations when assuming no gimbal lock degeneration.

Sensor displacement normally leads to a new signal space. In this new space the sensor readings likely differ with respect to those expected from a default or predefined sensor placement. These changes propagate through the different stages of the activity recognition chain (Section 3), thus affecting the inference process. An example of such effects is depicted in Figure 1. Here, a sensor displacement unintentionally introduced by the user when self-attaching the devices (Figure 1(a)) translates into a significant drift at the feature level (Figure 1(b)). Consequently, a model trained under the assumption of an ideal placement of the sensors (and accordingly a bounded feature space) may not normally cope with the variations introduced by the new feature space.

Other factors that also influence the magnitude of the displacement effects are the sensor on-body location (initial and final) and the magnitude of the motion experienced by the affected sensors. Thus for example, the drift may be pronounced when the sensor is displaced from the extreme of a limb (highly motional) to a position closer to the trunk (more limited mobility) when energetic activities are performed. On the contrary, during inactivity or while resting this change may not have appreciable consequences. Therefore, the effects are quite dependent on the particular activities, gestures or movements the user performs.

3   Activity Recognition Methods

Activity recognition approaches normally consist of a set of steps also known as activity recognition chain (an insightful review may be seen in [12]). Given a set of sensors positioned in different parts of the subject's body, these nodes are used to measure the motion experienced by each part. These records are translated into raw unprocessed signals that numerically represent the magnitude measured. Sometimes the signals are filtered out to remove possible anomalies such as electronic noise, however the information loss may be inappropriate in other cases. To capture the dynamics of the movements the signals are further segmented in partitions of a given size, normally through windowing or
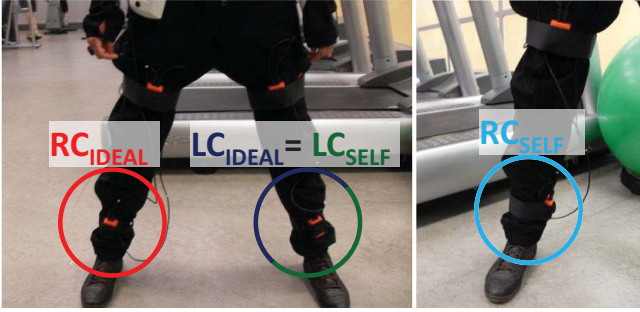
(a) Sensor displacement originated during sensor self-placement ($LC_{IDEAL} = LC_{SELF}$, $RC_{IDEAL} \neq RC_{SELF}$)
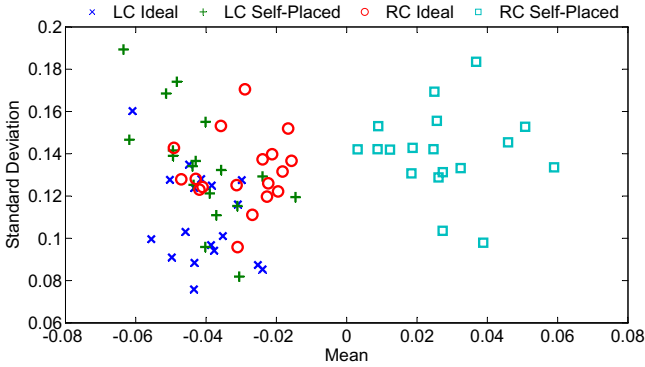
(b) Associated feature drift

Fig. 1. Example of sensor displacement introduced during the user self-placement (a) and its effect at the feature level (b). In this particular example the displacement from the default to the self-placement case applies to the right calf (RC) while the position remains roughly similar for the sensor attached to the left calf (LC). In (b) each mark represents an instance of the 'jump up' activity.

event/activity based techniques. Then a specific set of features are extracted from the data to provide a handler representation of the signals for the pattern recognition stage. A wide range of heuristics, time/frequency domain and other sophisticated mathematical and statistic functions are commonly used. The feature vector is provided as input to the classifier, ultimately yielding the recognized activity.

At this point, two approaches are proposed. The first one, here defined as 'feature fusion' corresponds to the case where all features coming from each individual sensor are combined on a single feature vector. This feature vector inputs a generic reasoning model. The second more sophisticated model [2] uses the individual feature streams extracted from each corresponding sensor and fuses the decisions obtained from the classifiers associated to every sensor. The so-called 'multi-sensor hierarchical classifier' is a technique that takes in the main advantages of hierarchical decision and majority voting models. Considering so,

the idea is to give all the decision entities the opportunity to collaborate on the decision making, but ranking the relative importance of each decision through the use of weights based on the classification entities individual performance.

4   Experimental Setup

For the evaluation of the proposed model an activity recognition bench-mark dataset is used [4]. This dataset is particularly appropriate for sensor de-positioning analysis because of its diverse displacement modes, amount of subjects and variety of activities. Namely, the dataset comprises motion data (tridimensional acceleration - ACC -, rate of turn - GYR - and magnetic field - MAG -) recorded for 17 volunteers while doing 33 'easy-to-perform' fitness exercises. The activity set defines from cardio-exercises such as running or cycling to general body movements like waist rotations ("hula hoop") or body-specific such as arms or knees bending. These exercises are performed while wearing a set of nine inertial sensors attached to different body parts.

Three scenarios in relation to the sensor displacement concept are considered: "ideal-placement", "self-placement" and "induced-displacement". The ideal-placement corresponds to the default or baseline scenario where the sensors are positioned by the instructor to specific well-identified locations (here on the middle of each limb and the back). A subset of the sensors is asked to be placed by the users themselves for the self-placement scenario, thus introducing a more realistic concept of daily sensor usage. Finally, the induced-displacement (also identified as 'mutual') constitutes the most troublesome scenario since intentional de-positioning of sensors is introduced by the instructor. This is of special interest to bench activity recognition solutions in conditions far from the default setup. These two last scenarios will normally lead to on-body sensor setups that differ with respect to the ideal-placement.

A subset of the original datasets is here considered. Ten of the most representative activities define the evaluation bench ($\{1, 4, 8, 10, 12, 18, 22, 25, 28, 33\}$, see [4] for equivalence). These activities apply to the all three datasets ('ideal', 'self' and 'induced'). Moreover, the experimental set includes the evaluation of each separated sensor modality (i.e., ACC, GYR and MAG) and their combinations. A segmentation process consisting of a non-overlapping sliding window (6 seconds size) is applied to each data stream. Mean, standard deviation, maximum, minimum and mean crossing rate are subsequently calculated for each window during the feature extraction process. C4.5 decision trees [6], which have been extensively and successfully applied in previous activity recognition problems, are used both for the multi-class classifiers and the binary or base classifiers components of the hierarchical approach. For the ideal scenario a tenfold random-partitioning cross validation process is applied across all subjects and activities. This process is repeated 100 times for each method to ensure statistical robustness. For both 'self' and 'induced' cases the procedure consists of testing a system trained in all 'ideal' data on the formers.

5   Results and Discussion

Figure 2 depicts the accuracy results for both feature fusion and multi-sensor hierarchical classifier. The evaluation of the models on the different sensor-placement scenarios (legend) is shown for each sensor modality or combination (X axis). The accuracy results demonstrate that the proposed methods are adequate solutions under the assumption of a fixed sensor setup. Nevertheless, it should be noted that both self-positioning and induced-displacement scenarios introduce a significant drop on the recognition systems performance with respect

(a) Feature fusion

(b) Multi-sensor hierarchical classifier
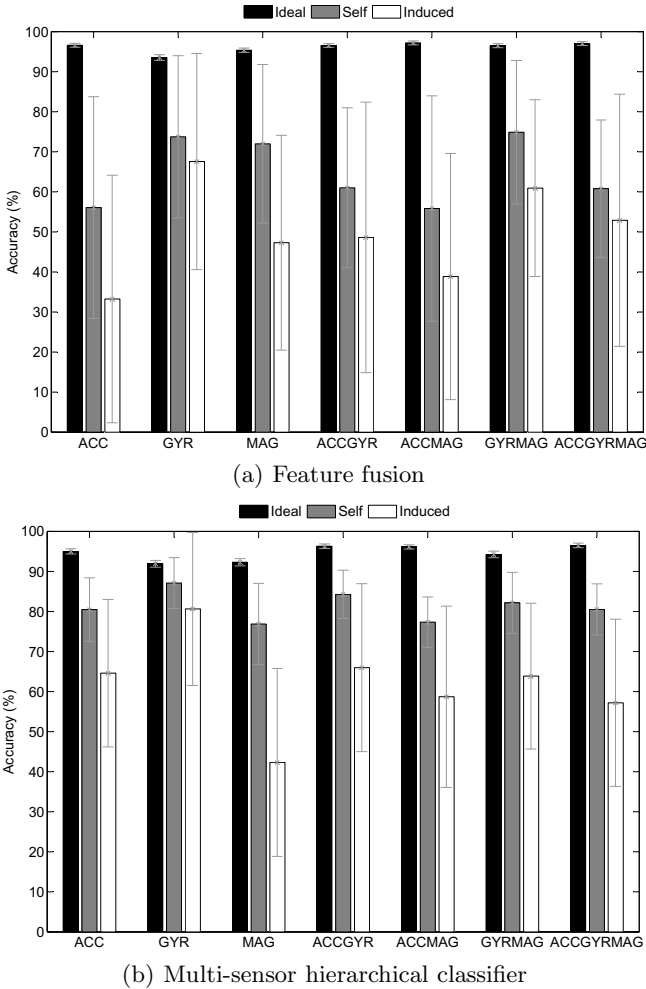
Fig. 2. Accuracy (mean and standard deviation) results from the evaluation of the a) feature fusion and b) multi-sensor hierarchical classifier when tested on the fitness dataset (the top legend identifies the type of sensor placement, see Section 4). Horizontal axis labels correspond to the sensor modalities used during the evaluation.

to the ideal or default scenario, which confirms the effects described in section 2. Clearly, the more profound the displacement applied ('induced' case) the higher the performance drop.

There are significant differences depending on whether the feature fusion or the multi-sensor hierarchical classifier are approached. When using the feature fusion (Figure 2(a)) it can be found differences with respect to the 'ideal' performance and the 'self' scenario that range from approximately 20% in the best case (GYR) to more than 40% at worst (ACC). This is more pronounced for the 'induced' case, where the variations go from 25% for the GYR to 65% again for the ACC based system. Thereby, it can be concluded that the acceleration modality is the most sensitive of the considered ones, followed by the magnetic field and rate of turn, with the latter the most robust magnitude. Now, the results for the hierarchical model (Figure 2(b)) are quite more promising. The comparison of 'ideal' and 'self' scenarios shows a performance drop of less than 5% for the GYR that increases up to 15% for ACC and MAG and at worst reaches 20% when both are combined (ACCMAG). The differences with respect to the 'induced' case spans from a bit more than 10% for the GYR to almost 50% when MAG modality is used. These better results for the multi-sensor hierarchical classifier may be explained since individual variations within a particular sensor with respect to its default behavior have less impact in the classification process. This is possible since each sensor contributes in an independent manner to the final delivered decision, so a majority of sensors (normally unaffected) overcomes the decisions provided by entities of affected sensors. Conversely, feature fusion models aggregate all features in a single data vector, thus leading to a potential feature drift that cannot be handled by the reasoning model. It can be concluded then that the hierarchical model prevails over the feature fusion approach.

6   Conclusions

In this paper we have compared two fusion mechanisms when dealing with sensor displacement effects. One of these approaches consists of a feature fusion that combines all features extracted from each sensor or node in a single feature vector that inputs to a simple decision tree classifier. This model demonstrates to not handle the data drift resulting from the sensors displacement. On the other hand, the second model constituted by a multi-sensor hierarchical classifier uses each sensor as individual inputs to independent decision entities that eventually concur on a recognized activity. This method turns to be more robust since displaced sensors have a lesser influence on the final decision when considered a minority. Future work aims to analyze the proportion of sensors to which the influence is satisfactorily overcome. Moreover some sensor modalities have been demonstrated more robust to displacements than others. Acceleration is the more sensitive whereas magnetic field and gyroscope are normally more robust, especially the latter. Combinations of inertial modalities do not necessarily lead to further improvement but to increase the complexity of the recognition system.

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