Dealing With Sensor Displacement In Motion-Based Onbody Activity Recognition Systems

Kai Kunze, Paul Lukowicz
Embedded Systems Lab, University Passau,
Innstr 43, 94032 Passau, Germany
www.wearable-computing.org
www.wearcomp.eu
kai.kunze/paul.lukowicz @uni-passau.de

ABSTRACT
We present a set of heuristics that significantly increase the robustness of motion sensor-based activity recognition with respect to sensor displacement. In this paper placement refers to the position within a single body part (e.g, lower arm). We show how, within certain limits and with modest quality degradation, motion sensor-based activity recognition can be implemented in a displacement tolerant way. We first describe the physical principles that lead to our heuristic. We then evaluate them first on a set of synthetic lower arm motions which are well suited to illustrate the strengths and limits of our approach, then on an extended modes of locomotion problem (sensors on the upper leg) and finally on a set of exercises performed on various gym machines (sensors placed on the lower arm). In this example our heuristic raises the displaced recognition rate from 24% for a displaced accelerometer, which had 96% recognition when not displaced, to 82%.

Author Keywords
Sensor Displacement, Opportunistic Activity Recognition, Motion Sensors, Fitness Exercises

ACM Classification Keywords
I.5.2 Design Methodology, Feature evaluation and selection

INTRODUCTION
Motion sensors, in particular accelerometers, are a common type of body worn sensors for activity recognition. Following the original work by Randell [12], Van Laerhofen [15] and Mantyjarvi [8] there have been numerous publication dealing with applications ranging from dance [1] through sign language recognition [2] to tracking of every day activities [5, 14] to industrial maintenance [11] and mental health related applications [17].

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An important question related to motion sensor based activity recognition is sensor placement and displacement. The vast majority of research in this area assumes well defined, fixed sensor locations. This is particularly important for activity recognition related to arm and hand motions.

Being able to drop the requirement for 'well defined fixed position' and build systems that can deal with sensor displacement has two major advantages:

- Robustness. During long term deployment sensor shifts cannot be avoided. Enabling the system to continue working correctly despite sensor shift is a significant improvement to robustness.
- Better usability and user acceptance. Today, many mobile appliance are already equipped with sensors. Sensor encapsulation into clothing or unobtrusive attachment e.g, as 'buttons' has been demonstrated [13]. It is thus often taken for granted that users can be easily equipped with sensors in every day situations. However, this does not imply that the user can be expected to reliably and firmly fix the sensors to narrowly defined on-body locations.

Problem Specification
The problem of on-body sensor placement can be decomposed into three sub-problems: (1) 'body part' placement, (2) sensor orientation, and (3) exact position within a body part,

'Body part' placement.
A user can carry mobile appliances such as phones and MP3 players in distinctly different body locations. The devices can be in a front or side pocket, attached to a belt, or in a holder on the upper or lower arm (e.g, during exercise). Except for trivial recognition problems (e.g, distinguishing walking from standing) a motion based recognition system trained on one body part will not work on another. However, we show that it is possible to reliably recognize the body part location of an accelerometer [4]. At the same time, for most appliances, there are a few body parts on which they can be placed. Thus, a system can be trained for several body locations and the appropriate version can be selected on the basis of the recognized location.

Sensor orientation.

It is well known that a static 3 axis accelerometer can be used to detect its own orientation with respect to gravity [10]. This means that with two simple calibration gestures we can determine the orientation of an accelerometer on a body part. For an arm mounted device, the user would have to hold the arm vertically and horizontally for a second or two. For most other body parts (upper body, leg) just standing still would be sufficient. Mizell has also shown that averaging over the signals on each axis over a reasonable time period can produce a good estimate of the gravity-related component [10]. During activities such as walking, where the type of motion performed by different body parts is constrained and well known, this could be used to automatically detect the orientation.

In summary, while handling orientation would certainly have to be carefully considered for each specific application and body part, there are a number of promising approaches that can be applied. As a consequence this paper make the assumption that, in most cases, orientation can be estimated with reasonable effort. Thus we concentrate on the variations of the exact position within the body part.

Exact position within a body part.

Most attachment methods leave a lot of room for placement within a body part. Thus, for example, arm MP3 holders often used for jogging can be placed almost anywhere on the upper or lower arm. Integration of sensors in clothing can ensure that sensors end up on a certain body part. However, it cannot ensure a specific placement on that body part. Even a tight fitting sleeve can be rolled up or twisted, completely changing the placement of any integrated sensors.

Unfortunately the within body placement issue cannot be solved with simple calibration gestures. As explained in the next section, the gravity component (=orientation) does not depend on the position within a body part. Thus, a static calibration gesture is not sufficient. Instead motions would have to be performed with *different, exactly defined speeds and trajectories.* In general we cannot expect the user to be able to perform such exactly defined motions with sufficient reliability.

In summary, regarding the three sub-problems described here, displacement within a body part is the most difficult to handle. Dealing with it is a so far unsolved problem. It is this paper's topic.

Paper Idea and Contributions

Although we did not discover an exact, always valid solution, we present a set of heuristics that significantly increase the robustness of motion sensor-based activity recognition with respect to sensor displacement within a single body part. We show how, within certain limits and with modest quality degradation, our heuristics allow motion sensor based activity recognition to be implemented in a displacement tolerant (within body part) way. Thus, within a single body part, we demonstrate reliable recognition at locations different from those on which the sensor was trained. The idea behind our approach is based on three observations:

1. The signal of an body-worn accelerometer is the sum of three components: acceleration due to rotation, acceleration due to translation and acceleration due to orientation with respect to gravity. Of the three only the first one: acceleration due to rotation is sensitive to sensor displacement within a single body part, as we will explain in the next section exploring the physical considerations our work is based on.

2. It is possible to identify, with high probability, accelerometer signal segments which are dominated by rotation and thus are possibly 'contaminated' with displacement related noise.

3. Gyroscopes are insensitive to displacement within a single body part but provide only information on rotation ignoring translations and vertical orientation.

From the above observations, it follows that combining a gyroscope with an accelerometer and having the accelerometer ignore all signal frames dominated by rotation can remove placement sensitivity while retaining most of the relevant information. In fact, sometimes just an accelerometer ignoring the rotation 'contaminated' frames can be enough for more displacement tolerant recognition. Additional measures that we propose are the use of heavily low pass filtered acceleration signals as additional features and training the system on two sensors corresponding to the 'worst possible displacement'.

The main limits of the validity of our heuristics are (1) a rigid body approximation of human body parts and (2) the assumption that the **bulk** of the discriminative information is **not** in signal segments that contain **simultaneously** performed fast rotations and significant translations or changes in vertical orientation.

In the rest of the paper, we first described how our heuristics can be derived from basic physical considerations. Next we apply them to a set of 'synthetic' gestures that are well suited to demonstrate the strengths and limits of our approach. Finally, we present an evaluation on two real life recognition tasks. The first task is an extended modes of locomotion problem using upper leg mounted sensors. The second is a set of gym exercises classified using sensors mounted on the lower arm. On this set our heuristics improves recognition rates for displaced sensors from 24% using a displaced accelerometer, which had 96% recognition when not displaced, to 82%. On other examples the displaced recognition rate raises from 63% to 90%.

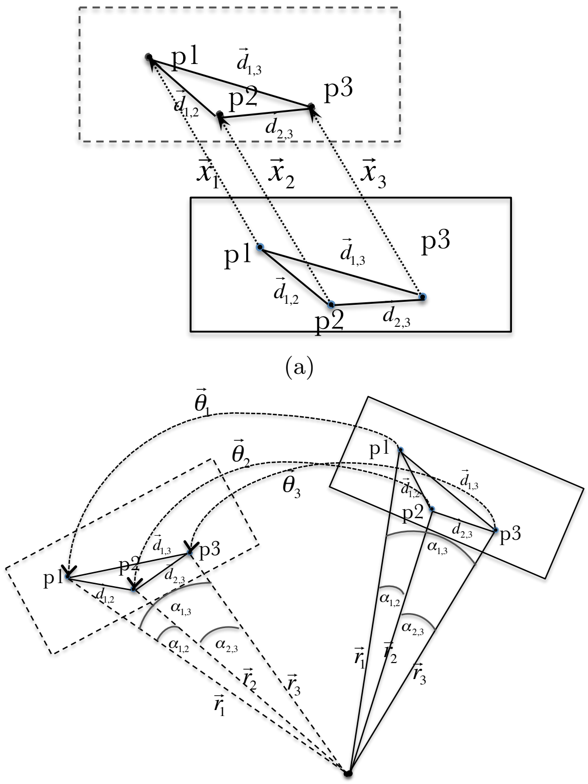


Figure 1: Rigid body translation 1a and rotation 1b

Related Work

To our knowledge there is no other work directly targeting the problem of within body part displacement for motion sensors. However, there has been some indirectly related work. Van Laerhoven presents a study to explore the trade-offs between single on-body sensors with predefined, well-known placement and an increasing quantity of sensors with decreasing information quality (placement accuracy) [16]. Zinnen presents an innovative way to use rest periods in accelerometer signals for detection of non-repetitive tasks which is based on some of the principles presented here [18] . Lester uses acceleration signatures to determine that a set of devices is being carried by the same person [6]. There is also some work on evaluating the suitability of different on body locations for activity recognition [9]. A platform with multiple sensors (in addition to mere motion sensors) has been investigated with respect to on body location invariance of activity recognition [7].

PHYSICAL CONSIDERATIONS

The Rigid Body Approximation

A common approximation used in modeling human body motion is that of rigid segments connected by joints which allow rotation around one (e.g. elbow) or more (e.g. wrist) axis. In simple words such an approximation is equivalent to a 'stick figure' representation used in many animations. In exact terms, a rigid body is an ideal solid body of finite size for which the relative position of any two given points remains constant in time regardless of external forces exerted on it. Any motion of a rigid body can be described as a combination of a translation and a rotation.

Note, that although human joints have only rotational degrees of freedom, a motion combining simultaneous rotation at two different joints can have the effect of a translation (e.g. shifting your lower arm through a combined elbow and shoulder motion). It is also important to keep in mind that motions involving more then one joint can lead to rotations around axis that are not identical with any of the involved joints. Regarding arm motions, such axis are often close to the torso, as we move our arms around the body.

Rigid Body Translation

During a translation every point in a rigid body is moved by exactly the same *vector* with exactly the same speed and acceleration. This is illustrated in figure 1a. We have a rigid body with three arbitrary points p_1, p_2, p_3. The relative positions of those points are given by the difference vectors $\vec{d}_{1,2}, \vec{d}_{1,3}, \vec{d}_{2,3}$. We assume that the body is translated (=moved in a straight line) randomly which results in p_1, p_2, p_3 being moved by a corresponding vectors $\vec{x_1}, \vec{x_2}, \vec{x_3}$. Per definition of a rigid body the relative positions given by $\vec{d}_{1,2}, \vec{d}_{1,3}, \vec{d}_{2,3}$ must remain unchanged. This is only possible if all the points are moved by exactly the same vector:

$$\vec{x_1} = \vec{x_2} = \vec{x_3} \tag{1}$$

This is valid independently of the translation distance and the time it took. Thus, given a translatory motion, at any point in time during this motion, all points of a rigid body will have been moved by exactly the same vector. This is also valid for infinitesimaly small time intervals which implies that at any given point in time the speed and with it the acceleration vectors will also be the same for all points.

Rigid Body Rotation

In an analogous way it can be shown that *angular velocity vector* (and angular acceleration) are the same for all points of a rigid body during a rotation around an arbitrary point in space. To illustrate this figure 1b shows a rigid body in which three arbitrary points p_1, p_2, p_3 and an arbitrary center of rotation r have been marked. The vectors connecting each point to the center of rotation are marked as $\vec{r_1}, \vec{r_2}, \vec{r_3}$, their relative angles as $\alpha_{1,2}, \alpha_{1,3}, \alpha_{2,3}$. We consider a rotation around r which results in p_1, p_2, p_3 being rotated by $\theta_1, \theta_2, \theta_3$. Since per definition of a rigid body after the rotation the relative positions of the three points given by $\vec{d}_{1,2}, \vec{d}_{1,3}, \vec{d}_{2,3}$ must be unchanged, the relative angles between vectors connecting them to the center of rotation $\alpha_{1,2}, \alpha_{1,3}, \alpha_{2,3}$ must also be unchanged. This is only possible if all three points have been rotated by the same angle:

$$\theta_1 = \theta_2 = \theta_3 \tag{2}$$

As for translation considering infinitesimal time periods, the angular speed ω and acceleration must also be the same for all three points.

In summary, during a rotation of a rigid body around an arbitrary point in space a gyroscope will produce the same signal no matter where in the rigid body it is placed. As will be explained later, this does not apply to accelerometers since different points in a rigid body in general experience a *different, non zero acceleration vector* during a rotation.

Limits of the Rigid Body Approximation

Obviously ,the individual segments of the human body are not really rigid bodies. Deformation of soft tissue, skin motion and muscle activity associated with most motions all lead to deviations. However, as will be underscored by subsequent experiments (see the next section), for many sensor positions and motions it is a valid approximation. The main deviations from the rigid body approximation can be observed in the following situations.

1. During short, intensive acceleration and follow up vibrations soft 'wobbly' parts (fat, soft muscles) are deformed in a non rigid way. To deal with such deviations the system might discard such vibrations.

2. When active muscles change shape. In particular large muscles will cause motion signals incompatible with the rigid body approximation. Thus, one should for example avoid placing sensors directly on top of a well developed biceps. Fortunately, such placement is often not very comfortable and is likely to be automatically avoided by many users.

3. The lower arm rotation parallel to the axis of the arm will affect sensors fixed to the wrist in a significantly different way than sensors near the elbow. The wrist sensor will rotate perfectly with the wrist, whereas the elbow sensor will do so to a much lesser degree. Gestures, for which such rotations are an important discriminative information are a problem for our location invariant recognition, are illustrated by our 'synthetic gestures' evaluation in Section .

Acceleration during Rigid Body Rotation

During a pure translation gyroscopes will provide no signal at all (there is per definition no rotational component) while accelerometers will all give the same readings no matter where they are placed.

As already said, in a rigid body all points are rotated with the same angular velocity (ω) and experience the same angular acceleration α. Thus, the gyroscope signal is invariant with respect to sensor displacement.

To understand the effect of sensor displacement during rotation on the accelerometer signal we need to revisit some basic physics. During a rotation with the angular velocity ω, the linear velocity v of each point of the rigid body depends on the distance from the center of rotation r. The further the point is from the center, the larger the circle it needs to travel and, consequenctly, the faster it needs to move. For the speed we have:

$$v = \omega r \tag{3}$$

The important thing to remember when looking at the above equation is that the v designates the speed traveled along a circle. This means that, although the scalar value of the speed is constant (if ω remains constant), to follow the circle each point of a rotating rigid body constantly needs to change its direction[1]. Such a change of direction requires an acceleration. The direction of the acceleration is parallel to the radius of the circle. The magnitude of this acceleration depends on the speed (the faster a point travels the more force is required to change direction) and with it on the distance for the center. The magnitude of linear acceleration a_ω due to constant angular velocity ω in a point at the distance r from the center of rotation is given by:

$$a_\omega = \omega^2 r \tag{4}$$

This gives us the first source of acceleration during a rotation of a rigid body. It is often referred to as centripetal acceleration. The second potential source stems from changes in the rotation speed. Since the linear speed is proportional to the angular velocity and the distance from the center (equation 3), it follows that the linear acceleration a_α associated with a change of angular velocity is proportional to the angular acceleration (α) and the distance from the center r:

$$a_\alpha = \alpha r \tag{5}$$

This component is called tangential acceleration.

Since the centripetal acceleration and the tangential acceleration are perpendicular, not parallel, the scalar values given above can not be just added to get the total magnitude of acceleration (which is the euclidian norm of the acceleration vector). For the sake of simplicity we will just deal with each of them separately [2] Another simplification is to ignore the coriolis force which acts on objects moving along the rotation axis. By moving more than one joint at a time, it is certainly possible to construct motions of human body parts for which the coriolis acceleration plays a significant role. Yet, motions where this is a relevant component are seldom and will not be discussed it in this paper.

Consequences for Displaced Sensors

What does the above mean for the noise introduced by displacing a sensor within a single, rigid body segment? As already state a gyroscope signal is displacement invariant so it need not be considered further. For an acceleration signal we need to differentiate between three contributions: (1) the contribution caused by orientation with respect to gravity, (2) the contribution caused by translations and (3) contribution caused by rotation. As explained above, the first two are location invariant and only the rotation component is location sensitive.

[1]The vector $\vec{v}$ is parallel to the tangent of the circle in each point of the rotation

[2]Since the two are perpendicular their contribution to the norm of the acceleration $a_{combined}$ is given by $\sqrt{\omega^4 r^2 + \alpha^2 r^2}$

Displacement Noise in Rotation Related Acceleration

Given two different points of a rigid body: one with a distance r_1 from the center of rotation and the second one with a distance of r_2, we can compute the acceleration components resulting from constant rotation $a_{\omega,1}, a_{\omega,2}$ and from angular acceleration $a_{\alpha,1}, a_{\alpha,2}$ from equations 4 and 5. Thus, the signal difference attributed to sensor displacement can be computed as

$$a_{\omega,1} - a_{\omega,2} = \omega^2 r_1 - \omega^2 r_2 = \omega^2 (r_1 - r_2) \tag{6}$$

$$a_{\alpha,1} - a_{\alpha,2} = \alpha r_1 - \alpha r_2 = \alpha (r_1 - r_2) \tag{7}$$

How relevant this difference is to the recognition depends not on its absolute magnitude, but on the signal to noise ratio. This is the ratio of the original signal ($a_{\omega,1}$ or $a_{\alpha,1}$) to the difference caused by displacement ($a_{\omega,1} - a_{\omega,2}$ or $a_{\alpha,1} - a_{\alpha,2}$. It can be computed from equations 6 and 7:

$$\frac{a_{\omega,1} - a_{\omega,2}}{a_{\omega,1}} = \frac{\omega^2 (r_1 - r_2)}{\omega^2 r_1} = \frac{r_1 - r_2}{r_1} \tag{8}$$

$$\frac{a_{\alpha,1} - a_{\alpha,2}}{a_{\alpha,1}} = \frac{\alpha (r_1 - r_2)}{\alpha r_1} = \frac{r_1 - r_2}{r_1} \tag{9}$$

The above is a very compelling result. It shows that sensor displacement noise during rotational movement depends only on the amount of displacement *with respect to the center of rotation*). It is independent of the actual angular velocity or angular acceleration.

Consequences for the Recognition

Previous paragraph dealt with the distortion of the acceleration signal related to rotation, as the other components are not affected by displacement. A naive idea for the design of an displacement invariant recognition system would be to try to ignore the rotation related component of the acceleration signal and use only the translation and vertical orientation related components.

Unfortunately in general [3], it is theoretically not possible to decompose an acceleration signal into the above three components. Note that this remains true even if we combine an acceleration sensor with a gyroscope. The gyroscope will indicate the presence and speed of rotation. However, as shown in equation to compute the acceleration we need the distance from the center of rotation, which we do not know.

Fortunately, although we do not know the exact radius of the rotation, we know that it is bounded by the dimensions of the human body. While rotational motions with very high radius can be constructed, for most human limb motions the center of rotation is somewhere close to the torso. This means, that for a given rotation speed, the acceleration is unlikely to exceed a certain value. This in turn means that we can use the ratio of rotation velocity measured by a gyroscope to the norm of the acceleration vector computed from the acceleration sensor signal to determine if the acceleration signal is rotation dominated or not. A high acceleration with a relatively low measured angular velocity is a good indication of the signal not being dominated by rotation. On the other hand, high angular velocity with low or moderate acceleration is an indication of a rotation dominated motion.

The ratios of angular velocity to acceleration norm signifying the transition between rotation and translation dominated signal depend on the typical rotation radius and with it on the motions relevant to the specific recognition task. They have to be learned during training. We will show an example in the next paragraph.

The above means that while we can not separate the individual components of a given acceleration signal, it is possible to estimate with reasonable probability which signal frames are dominated by rotation and which are not. We can then throw away the rotation dominated frames, which are sensitive to displacement and use only the ones dominated by translation and or vertical orientation. In a sensor setup with a gyroscope we can try to substitute the rotation for the thrown away acceleration frames to retain rotation related information.

Another interesting consideration relates to the vertical orientation component of the acceleration signal. Any (non free falling) object on earth is subject to a constant 9.81 m/s^2 acceleration. This means that if the norm of the acceleration signal is close to 9.81, then the signal is likely to be dominated by the vertical orientation component. Clearly this also is a heuristic that is not always valid. We can imagine a situation when an object is free falling while experiencing a 9.81 m/s^2 side acceleration. However this is a rare occurrence, and the above assertion is mostly valid (as will be underscored by the experiments in the next section).

In Summary

Signal Level Summary

The results of the discussion presented in this section can be summed up in the following points:

1. Gyroscopes are insensitive to sensor displacement within a single rigid body segment. However they capture only information about the rotational motion component. They fail to capture information about translational motions and the vertical orientation (orientation with respect to gravity).

2. The accelerometer signal is a sum of acceleration due to rotation, acceleration due to translation and acceleration due to orientation with respect to gravity.

3. Acceleration due to translation and orientation with respect to gravity are independent of sensor placement within a rigid segment of the body.

4. Acceleration caused by rotational motion is location sensitive. The ratio of the corresponding acceleration

[3] The general case assumes that there is no additional information such as further sensors in different locations on the same body part or appropriate high level knowledge about the form and constraints of the motion

signal to the 'noise' introduced by sensor displacement is proportional to the ratio of to the amount of displacement *with respect to the center of rotation.*

5. Using an acceleration (and possibly gyroscope) sensor at one location only, it is not possible to separate the three above mentioned acceleration components (rotation caused, translation caused and gravity caused). Thus, given an acceleration signal we are not able to remove the rotation related component (which is sensitive to displacement noise) and just use for classification the two other components (which are not displacement sensitive).

6. However, given an acceleration and a gyroscope measurement (from the same location taken at the same time), we can estimate the contribution of each of the three components to in the following way
   - If the norm of the acceleration vector is close to 9.81 (earth gravity) then the signal is most probably dominated by the gravity component (vertical orientation).
   - If the norm of the acceleration vector is not close to 9.81 then we look at the ratio of the norm of acceleration minus 9.81 to the angular velocity and the angular acceleration. If the angular velocity or angular acceleration dominate the ratio, we know that the acceleration signal is dominated by the rotation related components. Thus the acceleration signal is strongly location dependent. If the acceleration norm (minus 9.81) dominates, then we know that the acceleration signal is determined by translation related acceleration. In this case the acceleration is reasonably location independent.

   If none of the above applies then the acceleration signal is an mixture of the three contributions with none clearly dominating.

7. Low pass (pass frequency below Hz) filtered acceleration signal is likely to be dominated by the gravity component (see [3]).

Recommendation for recognition

For the design of on body activity recognition system based on motion sensors that is as insensitive as possible to sensor displacement, the following recommendations can be made:

1. If the relevant activities are mostly determined by rotational motions then placement invariance (within a rigid segment of the body) can be achieved by using gyroscopes instead of accelerometers.

2. For general activities the best location insensitive sensor setup consists of an accelerometer and a gyroscope. The procedure can be summarized as follows

   (a) If there is a significant gyroscope signal then we use it as primary source of information

   (b) To decide what to do with the accelerometer signal we look at the ratio of the total acceleration (norm of the acceleration vector) to the total rotation (norm of the angular velocity vector). The accelerometer signal is used for classification if it dominates both ratios. Otherwise it is ignored (e.g acceleration input to the classifier set to 0).

   The above procedure 'looses' information in two cases. First, if we have a motion that combines fast rotation or large angular acceleration with a significant amount of linear acceleration then the above rule leads to the acceleration signal being ignored. This is the price that we have to pay for location invariance and there is nothing that can be done about it. Second, in all cases where there is a large rotation we loose information about vertical orientation. Using strongly low pass filtered acceleration signal as an additional feature can, in most cases, retain at least some of the vertical orientation information.

3. If only an accelerometer is available, then the best we can do is to identify the segments of the signal that are dominated by the gravity component and base the recognition solely on the information about vertical orientation. This may sound like loosing a lot of information, however previous work ([3,18]) has shown that many activities are to a large degree determined by vertical orientation and changes thereof.

4. Independent of the recognition modality training the system with two sensors as far displaced as possible should encourage the classifier to focus on location invariant parts of the signal.

EVALUATION ON SYNTHETIC MOTIONS

As initial evaluation we look at following 8 'synthetic motions" of the forearm:

a move up
b move straight out
c move from left to right
d close elbow joint
e move back (closing elbow joint) and turn wrist in one motion
f turn around shoulder joint (screw-driving)
g turn large circles around shoulder
h turn smaller circles around elbow

The above motion set was put together to contain both 'easy' and 'hard' gestures and illustrate the strengths and weaknesses of our approach. Thus, for example, gestures e and d differ mostly in the turning of the wrist. As has been discussed in the previous section, wrist turning is especially displacement sensitive because of deviations from the rigid body approximation. On the other hand gestures a and b are likely to be well suited for our approach. Note that many typical arm activities are likely to contain motions from the above set.

The lower arm was chosen for two reasons. First, it is a likely place to wear accelerometers (watch etc.). Second, the forearm has the most degrees of freedom and is the body part that is able to move fastest.

Sensor Setup
We use XBus Master System together with 6 MTx motion sensors equipped with a 3-axis accelerometer, gyroscope and magnetic field sensors. As stated in the introduction we focus on the location within a single body part and ignore the question of sensor orientation. Thus, for all sensors, the x-axis orientation is the same (pointing towards the ground if the arm is in rest). The 6 sensor are placed as follows, (1) wrist outside, (2) wrist inside, (3) middle of segment outside (y axis orientation same as 1), (4) middle of segment on top of arm (y axis orientation 90 degrees to 3 and 1), (5) close to elbow inside and finally (6) close to elbow outside.

Signal Level Evaluation
Before we proceed to classification experiments we would like to use the synthetic gestures data to validate the basic assumptions behind our approach. First we check if leaving out signal segments with large angular velocity to acceleration ratio does indeed reduce the displacement related noise in the acceleration signal. To this end in Figure 2 (left) we have plotted the difference in signals between all sensors locations (in percent of the sensor signal) against the acceleration norm divided by angular velocity norm. In the rest of this paper we will refer to the difference in signals between all sensors locations in percent as displacement noise. It can be clearly seen that as long as the ratio is large (above 300) the signal difference is very close to zero. This means that displacement has nearly no effect on the signals. As the ratio gets smaller and angular velocity starts to dominate we begin to get a spread in the displacement noise and for very small values there is significant noise. This confirms our basic assumption.

Next, we check the assumption that frames where the norm of the acceleration is close to 9.81 (gravity) are likely to contain mostly orientation information and thus no displacement related noise. This is illustrated in Figure 2 (right). We can see that for accelerations norm values within 1g from 9,81 the noise is negligible.

In summary, our assumptions hold well on the test data set.

Recognition Experiments
Next we test if the validity of our assumptions will actually translate into recognition results. To this end we first train the system on two locations. We use two locations to be able to verify the claim that training different locations helps the system learn the displacement invariant features. We then test the system on the locations that it was trained on as well as on three additional locations. We do it with and without our heuristics and compare the results.

Classification Method
Applying 1 sec. sliding window we extract 45 standard pattern recognition features for each accelerometer and gyroscope axis. Concerning sensor orientation, we use normalized axis. For the evaluation of synthetic motions this is extremely simple, as most of the sensors have the same orientation anyway. For the later two evaluations two calibration gestures are performed between recording the motions. This allows us to determine two normalized axes from the accelerometers due to gravity. For all classifications we use the 2 normalized axis (defined as x and y) for feature extraction and only the magnitude of z, as we cannot determine its direction using the acceleration.

Modality	Same	Trained on 1	Trained on 2
Acceleration	100 %	33%	35%
Gyroscope	65%	43%	44%
Cut Off	-	42%	47 %
Combined	-	78%	85%

Table 1: Classification comparison for the synthetic motions using a majority decision over the motions based on a Knn classifier. Acceleration cut-off Norm - 9.81 at larger than 0.8. Decision Boundry for combining accelerometer and gyro at 300.

a	b	c	d	e	f	g	h	←
100	0	0	0	0	0	0	0	a
0	100	0	0	0	0	0	0	b
0	0	100	0	0	0	0	0	c
0	0	39.1	60.9	0	0	0	0	d
0	0	28.6	0	71.4	0	0	0	e
0	0	14.3	0	0	85.7	0	0	f
0	0	0	0	0	0	100	0	g
0	0	0	0	0	0	0	100	h

Table 2: Combined Accelerometer and Gyro trained on 2 evaluated on 4 Sensors Accuracy 85 %, Decision Boundary at 300.

Using the entropy measure also applied in the C4.5 decision tree, we reduced our feature set from 40 to 8 (mean, variance, number of peaks, median peak height, FFT center of mass, RMS, and frequency range power) depending on the evaluation. Each feature is calculated over the accelerometer and gyro data. The gyro data is normalized the same way as the accelerometer.

We classified all examples using several frame-by-frame classifiers(C4.5, KNN, BayesNets). As all of them show more or less comparable results, we pick KNN for the analysis for the remainder of the paper.

Classification Results
The results are summarized in table 1. Training the classifiers on training data and test data from one distinct sensor we reach a classification rate of 100 % using both frame by frame classification and a majority decision window over complete gestures. Testing the trained system on locations that it was not trained on reduces the recognition rate to 33% (on the accelerometer only). Having trained the system not on one, but on two widely displaced sensors improves the recognition rate to 35% only. Getting rid off frames with high acceleration improves the recognition by about 10% but the performance remains poor.

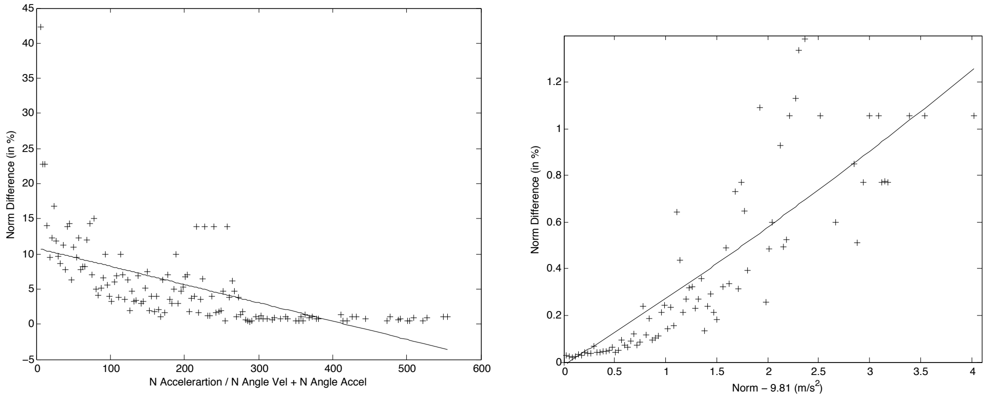


Figure 2: Left: Difference in Percent plotted against the Norm Acceleration divided by, the Norm Gyro Vector: Right Difference in Percent against acceleration norm - 9.81

The gyroscope performs significantly worse then the accelerometer (65% on the same location) confirming our analysis that it fails to capture all relevant information. When tested on a different location it drops to 43%. This is much less of a dramatic drop then for the accelerometers but still significant. We expected the gyro to be invariant with respect to displacement. The explanation is the inclusion of gestures with wrist rotation, which violates the rigid body assumption.

As expected best location invariant recognition results from a combined accelerometer/gyro based approach with all rotation dominated accelerometer frames being ignored. Trained on one sensor we reach 78%, on two we come up to 85%.

In summary the initial experiment confirms that our heuristic works well. Clearly 85% is far from perfect, but for many applications it may be acceptable (as opposed to 33%). The result is particularly significant because we were working with large displacements. Small displacements typical of 'slipping sensor' are likely to lead to a much less significant reduction in recognition rate (we have shown, that the noise is proportional to the displacement with respect to the center of rotation).

Another important thing to observe is the confusion matrix that corresponds to the 85% recognition rate (Table 2). It can be seen that out of the 8 gestures 5 achieve 100% recognition. The confusions involve gestures with significant wrist rotations. We have identified such rotations as one of the cases where the rigid body assumption underlying our heuristics is not valid.

MODES OF LOCOMOTION EXPERIMENTS

Towards more realistic evaluation we first look at an extended modes of locomotion problem with the sensors placed on the upper leg. We differentiate 8 activities (table 3) on the left. Note that this is not the trivial walking/standing/sitting modes of locomotion problem but an experiment involving fairly subtle differences.

Locomotion	Gym Exercises
i walking	q lat machine
j running	r pectorial
k running uphill	s shoulder press
l biking	t upper back
m rowing	u arm extension
n stairs	v arm curl
o skiing	w pull down
p crosstrainer	i chestpress

Table 3: Motions classified in the Locomotion and Gym exercise scenarios

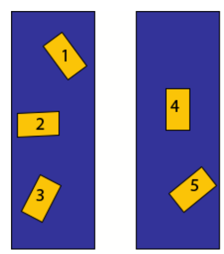


Figure 3: Random generated sensor placement and orientation for the leg(front and back).

Experiment Setup

The subjects upper leg is equipped with 6 MTx Sensors 3 mounted on the front and two on the back as seen in Figure 3. The placement is generated using a uniform random distribution. We use bandages to attach the sensors. Overall 8 locomotion classes (Table 3) were recorded on fitness machines in a fitness center. One test subject performed them each for 5 min.

Results

The results are summarized in table 5. Training and classifying on the same acceleration sensor gives an accuracy between 95 and 100 % using 10 fold cross validation or 66 % percentage split using a KNN and a majority decision window. As expected a gyroscope performs worse with 80 percent accuracy on the same location. Note that the leg motions are very much rotation de-

i	j	k	l	m	n	o	p	←
100	0	0	0	0	0	0	0	i
0	76.9	23.1	0	0	0	0	0	j
0	20.3	79.7	0	0	0	0	0	k
0	0	0	90.4	9.6	0	0	0	l
0	0	0	0	100	0	0	0	m
0	0	0	0	0	91.1	8.9	0	n
8.7	0	0	0	0	0	91.3	0	o
6.1	0	0	0	0	0	0	93.9	p

Table 4: Joint Accleerometer and Gyro trained on 2 Sensors eval on 3 90 % decision boundary at 150

Modality	Same	Trained on 1	Trained on 2
Acceleration	100 %	63%	65%
Gyroscope	80%	72%	75%
Cut Off	-	72%	76%
Combined	-	87%	90%

Table 5: . Classification comparison for the locomotion exercises using a majority decision over the motions based on a Knn classifier. Acceleration cut-off Norm - 9.81 at larger than 0.6. Decision Boundry for combining accelerometer and gyro at 150.

termined, so the performance reduction for the gyro is less pronounced than for the synthetic gestures from the previous paragraph.

Testing the same methods on a location on which they have not been trained leads to a recognition rate of 63% on the accelerometer and 72% on the gyro. As we have less deviations from the rigid body assumption the drop in gyro recognition rates is smaller than for the synthetic arm gestures. That it exists at all, is probably due to muscle motions (which are significant in some locations on the upper leg). Training on two locations brings minimal improvement. Restricting the acceleration frames to those with a norm close to 9,81 improves the recognition by 10% bringing it to 76% when trained on two sensors. This relatively good recognition rate (for a displaced, acceleration only system) is due to the fact that most of the relevant motions are largely determined by changes in vertical orientation of the upper leg.

The combined accelerometer gyro heuristic (throwing away rotation related acceleration frames) brings the recognition rate to 90% (trained on two sensors).

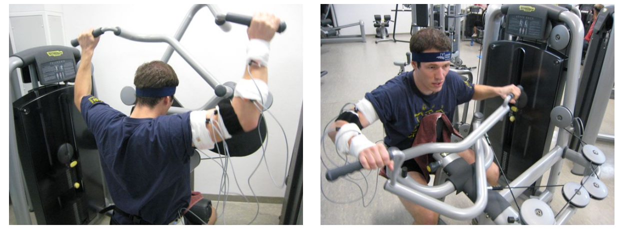
In summary, the modes of locomotion experiment also confirms the validity of our methods. For many practical applications the 90% recognition rate might be sufficient. Again one should keep in mind that we were working with large displacements and that the noise is proportional to the displacement.

GYM EXPERIMENTS WITH SENSORS ON FOREARM

The most challenging evaluation focuses on muscle strength exercises conducted at fitness center machines.

Experiment Setup

The sensor placement and orientation are generated random. There are 4 sensors at the forearm placed as follows. The first around 10 cm away from the elbow on the outside of the arm , x axis angle around 90°



(a) (b)

Figure 4: Two pictures form the gym experiment data recording

turned from an orientation that is parallel to the arm pointing towards the ground, the second on the wrist, with approximately 50°, the third placed at the inside of the arm around 8 cm away from the wrist with 0°, the forth placed also on the inside closer the the elbow at 10°. Again we picked 8 gym exercises to record, as shown in Table 3. One test subject performed each exercise 20 -25 times. Two runs were conducted.

The feature extraction follows the approach laid out for snythetic motions and leads to the same features. We use a 1 sec. sliding window. The recognition task is much harder than the modes of locomotion problem and the majority decision using the acceleration trained and evaluated on the same location gives only an accuracy of 85%. We have thus turned to a continuous HMM based approach. On top of the features extracted as mentioned above we apply another 15 sec. sliding window using 3 gaussians for each feature and 4 hidden states. In case of combining the gyro and accelerometer data, we picked the decision boundary at 300 for the ratio. If it is below the boundary we use the gyro features and set the accelerometer features all to zero.

Results

The results are summarized in table 6. When training and testing on the same location (again 66 % percentage split) we reach 96 % on the acceleration signal alone. Testing the acceleration only system on a location that it was not trained with drops the recognition rate to 24 %. This was to be expected, as the classification problem is fairly complex. The rate can be raised to 31% by training the system on 2 sensors, which is significant but not really useful. A gyro trained and tested on the same location gives an accuracy of 62% again confirming that the gyro signal 'looses information'. [4] However, a significant improvement on displaced sensor is achieved with our combined gyro/accelerometer approach. Trained on one sensor we reach 74% on two we come up to 82%. The confusion matrix for this case is shown in table 7.

Considering the confusion matrix of the combined accelerometer and gyro case, the really significant miss-

[4]Since the problem is harder than the previous ones it was not to be expected that dropping high acceleration frames form the accelerometer classification will lead to reasonable performance. Since the HMM evaluation was more time intensive than the majority decision from previous examples we did not take the time to evaluate this approach.

Modality	Same	Trained on 1	Trained on 2
Acceleration	97%	24%	31%
Combined	-	74%	82%

Table 6: Classification comparison for the gym exercises using a continuous HMM. Decision Boundary for combining accelerometer and gyro at 300.

q	r	s	t	u	v	w	x	←
75.6	0	0	0	0	0	0	24.4	q
0	81.6	0	0	0	0	18.4	0	r
0	0	88.6	0	11.4	0	0	0	s
0	0	0	100	0	0	0	0	t
0	0	13.3	0	76.7	0	10.0	0	u
0	0	0	0	22.2	77.8	0	0	v
12.0	0	0	0	8.0	0	80	0	w
0	0	0	20.8	0	0	0	79.2	x

Table 7: Confusion Matrix Joint Accleerometer and Gyro trained on 2 Sensors eval on 2 82 % decision boundary at 300

classifications happen between movements that train the complementary muscles, for example arm extension and arm curl.

CONCLUSION AND FUTURE WORK

We have shown that a combination of an accelerometer that ignores rotation dominated signal segments and a gyroscope to compensate for the lost rotation information is reasonably robust with respect to sensor displacement within a single body part. Combined with two sensor training to force the classifier to ignore location artifacts we have shown that randomly, significantly displaced sensors can reach up to abut 90% of the recognition rate of a non displaced sensor. Compared to testing an unmodified classification system on a different location we can improve the recognition rate by over 300% !

Clearly coming to 90% of the non displaced sensor will not be sufficient for all applications. Also the need to add a gyroscope (which is more expensive than an accelerometer) may not always be acceptable. However we believe that our heuristics are a significant improvement over the current state of the art and may be good enough in many cases.

This paper has focused on large displacement that would be typical of a user being given no instructions on where to place the device. We also wanted to test the limits of our ideas. Next we will investigate in more detail smaller displacements that my be more typical of shifted sensors. As described in the paper displacement noise is proportional to displacement distance. Thus for smaller displacements and with some further improvements we believe that our methods could work satisfactorily even for accelerometer only systems. Under such circumstances accelerometer/gyro system might be able to mask out displacement noise entirely.

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