Pre-impact fall detection
Abstract

Falls and fall-related injuries are among the most serious and common medical problems experienced by the elderly. Support could be given to prevent severe injuries from those falls. Therefore the design of a robotic assistive device is currently investigated in the MARS3-project. Such a device requires knowledge of the human posture to determine loss of balance. At the moment several methods are available to detect a fall, these are not accurate enough to be implemented into a robotic device. In this study a reliable trigger for a robotic device is investigated.

During an experiment in which participants performed a balance task, human movement is recorded. Motion Capture is performed to track the posture changes and a sensor system is used to obtain input for the assistive device. It is analyzed that the output of the sensory system is in correspondence with the movements recorded by Motion Capture.

Based on the Motion Capture the data is divided into stable and unstable phases. Six methods to design a classifier that is able to distinguish between stable and loss-of-balance are proposed. These methods are all trained and evaluated with the data sets obtained in the experiment.

The main measures to evaluate the performance of the algorithms are sensitivity, i.e. detect all instances of loss of balance, and specificity, i.e. no false alarms. Although the sensory information is in correspondence with the actual body movement, the proposed classifiers do all result in sensitivity and specificity rates that are not high enough to implement into an assistive device. The value of information is too low, it is not possible to distinguish stable and unstable phases by means of the proposed classifiers.
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Nomenclature

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<th>ADL</th>
<th>Activities of Daily Living</th>
</tr>
</thead>
<tbody>
<tr>
<td>A/P</td>
<td>Anterior/Posterior (forward/backward)</td>
</tr>
<tr>
<td>CoM</td>
<td>Center of Mass</td>
</tr>
<tr>
<td>CoP</td>
<td>Center of Pressure</td>
</tr>
<tr>
<td>IMU</td>
<td>Inertial Measurement Unit</td>
</tr>
<tr>
<td>M/L</td>
<td>Medial/Lateral (sideways)</td>
</tr>
<tr>
<td>MoCap</td>
<td>Motion Capture</td>
</tr>
<tr>
<td>$a_x$</td>
<td>Acceleration in x-direction</td>
</tr>
<tr>
<td>$a_y$</td>
<td>Acceleration in y-direction</td>
</tr>
<tr>
<td>$a_z$</td>
<td>Acceleration in z-direction</td>
</tr>
<tr>
<td>$\alpha_{\text{lean}}$</td>
<td>Lean angle in lateral direction</td>
</tr>
<tr>
<td>$\dot{\alpha}_{\text{lean}}$</td>
<td>Angular velocity in lateral direction</td>
</tr>
</tbody>
</table>

Body fixed reference frame

To describe all movements of the subjects trunk a body-fixed coordinate system is defined, see Figure 1. The x-axis points in medial-lateral (M/L) direction to the right, the y-axis in anterior-posterior (A/P) direction to the front and the z-axis equals the vertical directed to the head. The origin is located at the back, close to the center of mass.

![Figure 1: Body fixed coordinate system, x-axis M/L-direction, y-axis A/P-direction and z-axis vertical direction. By Edoarado via Wikimedia Commons](image-url)
1 Introduction

Degeneration of balance control is present in elderly and in many pathologies. It consequences an increase of effort for the affected human to prevent a fall. Because of this degeneration injuries and loss of life due to falls increase, as studied by Winter (1995) [1]. Balance control and falls are discussed in section 2.1 and 2.2. The severe consequences of fall-related injuries motivates the research of human balance and investigation of methods to support balance control.

Because two-third of the body mass is located at two third of the body height, the upright human body is an inherently instable system, comparable to an inverted pendulum. To maintain balance human motor control activities are continuously present to stabilize the body. This is further discussed in section 2.1.

This study is part of the MARS\textsuperscript{3} project\textsuperscript{*}. The purpose of that project is to improve balance control and reduce risk of falls by means of a robotic assistive system, see Figure 2. Development of a balance assistive device, which is based on a gyroscopic control output, is the ultimate goal of the coordinating project.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{robotic_device.png}
\caption{Artistic impression of robotic assistive device containing three gyroscopes}
\end{figure}

\textsuperscript{*}Machines Assisting Recovery from Stroke and Spinal Cord Injury for reintegration into Society - Rehabilitation Institute of Chicago (RIC)
1.1 Study goals

The scope of this project is more narrow than the coordinating project. This section provides the study goals and constraints of the project. The research questions and study goals are related to the main objective:

In this study a reliable trigger for a robotic device is investigated.

To investigate the trigger the following research questions are set.

• Validity of the sensor; is the sensory information in correspondence with the actual body movement?
• What is the value of information; with respect to the ability to distinguish stable and unstable phases?

The purpose of the assistive device is to reduce the risk of fall related injuries. This study focuses on the ability to balance in sideways direction, because of the severe consequences of a sideways fall. An experiment in which balance is challenged, is performed by young participants. The validity of the proposed sensor system, which is implementable into the robotic device, is evaluated by means of a comparison between sensor output and estimations of human posture based on 3D-motion capture of the subject. A novel algorithm to distinguish stable and unstable phases is applied. Besides this novel algorithm, the generated data is used to verify algorithms as presented in papers by different authors. In order to evaluate the specificity, only trigger in case of a fall, Activities of Daily Living (ADL) are performed to obtain data of stable phases.
2 Background

In this section background information is given related to human balance control strategies. A coherent overview is given including postural control, falls and support. At first mechanisms of human postural control are described in section 2.1, when postural control fails a fall can occur. Falls and the possible consequences are given in section 2.2. To prevent severe injuries from those falls support should be given, see section 2.3.

2.1 Postural Control

Hof (2007) described three strategies to control human posture [2]. Two of these strategies refer to the joint about which most of the movement occurs, as described by Rietdyk (1999) [3]; the hip strategy, and ankle strategy. The third strategy refers to an external force, as when the human holds on to a handrail.

The ankle strategy is related to movement of the center of pressure (CoP), because the mechanism by which balance is maintained is based on movement of the CoP in such a way that the center of mass (CoM) is moved to within safe boundaries of the base of support (BoS). The locations of the CoP, CoM and BoS are shown in Figure 3.

![Figure 3: Position of the Center of Mass (CoM), the Center of Pressure (CoP) and the Base of Support (BoS)](image_url)

Figure 3: Position of the Center of Mass (CoM), the Center of Pressure (CoP) and the Base of Support (BoS)
The hip strategy is related to ‘counter rotation’, because parts of the trunk are rotated around the hip with respect to the CoM. This strategy is used where the ankle strategy is not sufficient to maintain balance. Because of the conservation of angular momentum the ‘counter rotation’ causes the body to rotate in opposite direction.

Next to these strategies Pijnappels (2009) found arm movements to play a functional role in balance recovery [4], as a counterweight to shift the CoM away from the direction of the fall or by generating a reactive torque which contributes to the ‘counter rotation’ mechanism.

### 2.2 Falls

When all strategies of postural control fail, a fall occurs. A fall is defined as an unintentional event which results in a person coming to rest inadvertently on the ground, floor or other lower level. In a home environment, in hospitals and in residential homes falls affect the overall quality of life. Fall-related injuries are among the most serious and common medical problems experienced by the elderly. This affect over one out of three elderly people [5], as found by Bourke (2007).

For several factors strong evidence is found to be a risk factor for falls [6], these risk factors are described by Delbaere (2013). The four most important risk factors for falls are impaired stability when leaning and reaching, impaired gait and mobility, impaired ability in standing up and impaired ability with transfers. These impairments can be caused by a disorder of the muscular system, such as weakened muscles, or a disorder of the nerve systems, such as impaired motor control. Next to the risk factors there are several direct causes of a fall. Falls could be caused by environmental conditions or are related to health. The most frequent cause of falling is incorrect weight shifting, seemingly self-induced shifting of bodyweight causing the Center of Mass to move outside the Base of Support.
2.2.1 Hip fracture

One of the most common fall-related fractures involves the hip, as found by DeGoede (2003). Most injuries in the elderly result from falls. Fracture is a serious injury associated with falls. Rivara (1997) found 87% of the fractures to be caused by a fall [7]. Fall direction and impact site are important factors affecting risk and type of injury. Falls in M/L-direction, slips and impacts at the hip are associated with hip injury. Approximately 18% of all falls is in M/L-direction, as observed by O'Neill (1994) [8], see Figure 4.

![Figure 4: Fall directions of older adults. Data from O'Neill (1994)](image)

The consequences of a hip fracture regarding residential needs and performance of ADL are serious, as observed by Osnes et al. (2004) [9]. Approximately a third of the patients has to move to a nursing home after a hip fracture. The need for a walking aid increased from 24% to 64% in a year after injury and many patients have reduced ability to perform ADL.

2.2.2 Reduce risk of fall related injuries

The risk of serious injury is related to biomechanical factors [10], as presented by De Goede (2003). To reduce the risk of fall related injuries, one or more of these factors have to be modified. It is important to gain insight in which factors are modifiable and which are not.

Intrinsic factors, those that belong to the human, that are not modifiable are: strength of the bone, soft-tissue thickness and reaction time. Extrinsic factors, those that belong to the environment, that are not modifiable by an assistive device are; fall height and initial speed at the instance the human loses balance.

Factors that are modifiable are fall direction, orientation of the body parts, contact point with the ground at impact and velocity of the body segments. A lower velocity results in lower force during impact, which decreases the risk of serious injury.
2.3 Support

Single tip support cane and walkers are the most well known and mostly used walking aids [11], Bateni (2005). Evaluation of canes and walkers confirm that these devices may improve balance, however in certain situations they can also interfere with one’s ability to maintain balance. Studies show that 30% to 50% of older adults abandon their mobility aids soon after receiving it [11], as found by Bateni (2005). Such high rates of disuse motivates researchers to improve the mobility aids.

The most common fall detection system for elderly is an alarm button, a so called personal emergency response system (PERS). When the button is triggered, by the user, a signal is send to care givers. Bourke (2007) found the PERS to be not satisfactory because it is not always activated [5]; due to a loss of consciousness, injury, emotional distress or a faint. To reduce the medical consequences of a fall an automatic detection system is required, preferable a pre-impact system to reduce fall related injuries. The detection system can be implemented into a hip protector, i.e. a belt that inflates a protective air-bag, or an active support system, e.g. a backpack including a gyroscopic device.

2.3.1 Three detection objectives

There are three possible detection objectives for a system. The first one is post-impact fall detection, to enable care givers to provide aid after the subject has fallen. This is not within the scope of this study, since the focus is on pre-impact fall detection. The second one is pre-impact fall detection. Pre-impact fall detection detects when an individual is about to fall and measures can be taken to reduce the consequences of the impact. The third objective is also a kind of pre-impact detection, however this is not strictly associated with a fall as it detects loss-of-balance, a high risk of a fall or even the start of a true fall. Goal is to prevent a fall or at least to reduce the impact. This study focus on the third objective.
3 Fall detection

To trigger the alarm or give support as required, a fall detection system has to be designed. Such a system consists of a sensor system and an algorithm for classification. The characteristics of human posture and movement are measured by the sensor system. In the design of the system the type, location and associated metrics of the sensor have to be taken into account. Section 3.1 provides basic knowledge of sensors to track human posture. The classification, which aims for a dichotomous outcome, can be performed by different fall detection methods, as discussed in Section 3.2. Six algorithms are proposed in Section 3.3 to be investigated.

3.1 Sensors

Sensors provide raw data from which relevant information can be extracted. The three main problems regarding sensors are: noise, redundancy and limitations. In relation to noise the reliability has to be examined; whether the sensor is to be trusted or not. The signals of redundant sensors can be fused to combine their information. Sensors cannot always measure all required information; some of the variables have to be estimated. This section focuses on a specific type of sensor: Inertial Measurement Units, used to estimate the orientation of a body. The working principal, the metrics and the location of preference are covered in this section.

3.1.1 Inertial Measurement Unit

An Inertial Measurement Unit (IMU) contains both accelerometers and gyroscopes, this combination provides worthful information about the body’s orientation.

Accelerometers are used to measure acceleration in three perpendicular directions. Due to the gravity the signal in \( z \)-axis is \(-1 \text{ m/s}^2\), when stationary; whereas the signal in \( x \)- and \( y \)-axis equals \( 0 \text{ m/s}^2\). An accelerometer is not capable to distinguish gravity from the actual acceleration of the system. Therefore the difference between accelerating forward and leaning backward can not be distinguished by the accelerometer.

Gyroscopes measure the angular rate, i.e. speed of rotation. To obtain the angle of the system the signal of the gyroscope has to be integrated. Major disadvantage of integration is the drift over time of an integrated signal.

3.1.2 Metrics

The linear acceleration in direction of the three perpendicular axes, \((\ddot{x}, \ddot{y}, \ddot{z})\), is measured by accelerometers. To distinguish vertical acceleration of the body from the gravitational forces the absolute vertical inclination of the sensor has to be known. This is obtained by a magnetometer; the direction and magnitude of a magnetic field at a point in space is measured. The earth’s geomagnetic
field provides reference vectors for the calibration of the accelerometers. The angular velocity around the three axes are measured by gyroscopes, who are perpendicular to each other.

In the output of an IMU typically high noise levels and time-varying biases are present. This causes unlimited drift in the estimated values. Different methods are available to estimate the biases and update the values. The estimation of the orientation of a body can be algebraically reconstructed if two or more non-parallel inertial directions are available.

3.1.3 Sensor location

During movements the acceleration varies in different parts of the body. To capture all key features of a fall, the location of the sensor should be chosen carefully. It is preferable to attach the sensors near the Center of Mass (CoM), in order to provide reliable information of subjects movements. This preference is supported by Bourke (2007), who compared sensor located on the trunk and thigh [5], by Kangas (2008), who compared fall detecting algorithms with sensors at three different locations: waist, head and wrist [12], and by Liang (2012), who compared four different locations: waist, chest, shank and thigh [13]. Unfortunately, it is not possible to match this position with the sensor location, as the CoM is positioned inside the body.

Multiple sensors can be integrated into the design of an assistive device. The advantage of a combination of signals from sensors at different positions is the ability to construct additional information.

3.2 Fall Detection Methods

A literature survey is performed, in which methods for fall-detection are assessed. This section includes an overview of methods applied in earlier studies, a classification of these and a framework to enable a comparison of the methods.

3.2.1 State-of-the-Art

There are several approaches for fall detection algorithms. This section describes a total of ten methods.

Two methods, described by Nyan (2008), detect a fall based on the angle of body segments. The first method is based on the pitch and roll of the trunk [14], the second method is based on the angular position of thigh and trunk [15]. In both methods a threshold of 10 degrees deviation from the vertical axis for the angles is introduced, this is in congruence to the maximum lean angles [16] found by Carbonneau (2013).

Another approach is the use of the velocity of body segments. The velocity of body segments has unique features that can be used to distinguish loss-of-balance from stable phases. Unique characteristics in the horizontal and vertical velocity profiles, \( v_h \) and \( v_v \) respectively, are identified by Wu (2000). Peaks in \( v_h \)
and $v_t$ are limited within 1 m/s and peak velocities do not occur simultaneously during Activities of Daily Living [17]. These values are supported by Kangas (2007) who determined that the velocity of the waist in 95% of the falls is over 1.0 m/s [18]. Bourke (2008) found that a threshold of the vertical velocity of the trunk alone is sufficient to distinguish falls from ADL. The obtained threshold equals 1.3 m/s [19]. Besides linear velocity profiles the angular velocity can be used as measurement, for this purpose a gyroscope is required. The ability to distinguish sideways and backward falls from ADL using gyroscopes is investigated by Nyan (2006) [20].

A threshold on the norm of the acceleration is implemented into several algorithms. Liang (2012) measured at the waist [13], whereas located the sensor Bourke (2007) at the trunk and thigh [5]. A combination of the norm of the acceleration and the vertical acceleration is implemented by Kangas (2009) [21].

Feature selection, in which data segments are used instead of information of a single point in time, is applied in studies by Tong (2013) and Shan (2010). In the study by Tong (2013) Acceleration Time Series are used [22]. The method in the study by Shan (2010) also uses feature selection based on the acceleration of the body.
3.2.2 Classification

The diverse approaches for fall detection algorithms are often categorized according to the phase of the fall. Motion before impact is mostly measured by high velocity, fast posture change or free fall. Impact itself is measured by high acceleration or rapid change in acceleration. Or even after the impact occurred by capturing the end posture or general activity.

Since the focus of this study is on pre-impact fall detection, the former categories are not suitable; therefore another classification is chosen. The fall detection systems in which a threshold is implemented are categorized based on the measured variable of the body segment, such as angular position, horizontal, vertical or angular velocity and acceleration. Next to these threshold-based systems a set of relevant features could be selected to be used in a model. In table 1 an overview of the approaches is given.

<table>
<thead>
<tr>
<th>Author (year)</th>
<th>Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nyan (2008a)</td>
<td>Pitch and roll of trunk</td>
</tr>
<tr>
<td>Nyan (2008b)</td>
<td>Angular position thigh and trunk</td>
</tr>
<tr>
<td>Wu (2000)</td>
<td>Vertical and horizontal velocity</td>
</tr>
<tr>
<td>Bourke (2008)</td>
<td>Vertical velocity</td>
</tr>
<tr>
<td>Nyan (2006)</td>
<td>Angular velocity</td>
</tr>
<tr>
<td>Liang (2012)</td>
<td>Resultant acceleration waist</td>
</tr>
<tr>
<td>Bourke (2007)</td>
<td>Resultant acceleration trunk and thigh</td>
</tr>
<tr>
<td>Kangas (2009)</td>
<td>Resultant and vertical acceleration</td>
</tr>
<tr>
<td>Tong (2013)</td>
<td>Resultant acceleration time series and HMM</td>
</tr>
<tr>
<td>Shan (2010)</td>
<td>Feature selection and support vector machine</td>
</tr>
</tbody>
</table>

Table 1: State-of-the-art of approaches for fall detection

3.2.3 Evaluation

At the moment it is difficult to compare the performances of various fall detection methods based on literature data. Some common criteria for evaluation were used, but no common procedures were used to perform the tests. Therefore Noury (2008) found that it is very important to propose a framework for the evaluation of the fall detection methods [24].

The ‘quality performance’, the ability to detect all falls and only the fall events, is important. Both sensitivity and specificity rate have to be close to 1. The performance rate is strongly related to the chosen activities in the study. Therefore the performed movements in the experiment have to be evaluated, as studies do not compare the same type fall events and Activities of Daily Living (ADL).

To evaluate the ability to generalize the obtained classifier, the age of the participants has to be considered. The obtained classifiers are not always suitable to be generalized, due to the age of the participants. Older persons move
different from adolescents, while in most studies adolescents have participated as subject.

The moment of detection should be as early as possible. If a fall can be detected in its descending phase, before impact occurs, impact reduction systems can be implemented to minimize injuries. The performance of the system with respect to the phase of the fall in which the fall is detected is assessed by the lead-time. If a fall is detected before the impact occurred and support could be applied, one needs to know characteristics of the fall. To apply required support the process of the fall has to be detected. The ability of the fall detection systems is to be evaluated on this issue.

As an extension to the framework the subject compliance should be taken into account. In long-term unsupervised monitoring environments, Godfrey (2008) found subject compliance to be essential, with the monitor being as comfortable and unobtrusive as possible [25].

3.2.4 Subject-to-subject variability

Methods for the determination of thresholds can be classified into two types: empirically determined thresholds (experimental in a laboratory) and machine learning methods (include learning phase, real situations of use). For both methods of determination subject-to-subject variability has to be taken into account.

Since the subject-to-subject variability in human movement is high, threshold needs to be subject-specific, especially to distinguish the movement of elderly [26], as mentioned by Van Wegen (2002). To overcome this difficulty and obtain a subject-specific threshold a ‘learning period’ may be used, as suggested by Noury (2008) [24]. This learning period may be supervised by asking the wearer to carry out a series of voluntary movements in order to determine the normal characteristics of execution. If the learning period is unsupervised the movements of the person are simply recorded during a few hours or several days, and afterwards a statistical analysis on the measured signals has to be carried out.

3.3 Proposed classifiers

In this section six classifiers are proposed. The methods described in Section 3.2.1 are used to design novel algorithms. The thresholds are not set in the design, since they are based on the data obtained in the experiment.

In the first method the norm of the acceleration, $a_{\text{norm}} = \sqrt{a_x^2 + a_y^2 + a_z^2}$, is used as trigger. This classifier is based on a single variable to distinguish loss-of-balance from stable phases. This threshold is already implemented by Liang (2012) and Bourke (2007). The method is considered since the results are promising. It is not a novel algorithm, this study however differs since it aims to detect loss-of-balance instead of a fall.

It is assumed that a voluntary movement is performed primarily in one direction. This is supported by the observation that simultaneous peaks of linear
velocities only occur in a fall movement [17], as found by Wu (2000). Integration errors cause drift in the linear velocity signal, therefore the principle of simultaneous peaks is altered to peaks in the linear acceleration signal. Where the horizontal acceleration equals the square root of the acceleration in $x$- and $y$-direction; $a_{hor} = \sqrt{a_x^2 + a_y^2}$. The second method consists of a combined threshold; at the instance the thresholds of both horizontal and vertical acceleration are exceeded the system detects loss-of-balance.

Maximal lean angles while standing, from which recovery without a corrective step is possible, are measured by Carbonneau (2013) [16]. This provides the basis of the third method, in which the angular velocity in lateral direction ($\alpha_{lean}$) is used as single variable to trigger the system. As the inclination angle might not be accurate enough, the angular velocity is taken into account in the fourth method. In this method the angular velocity in lateral direction ($\dot{\alpha}_{lean}$) is used as single variable to trigger the system.

The fifth method combines the data of the lean angle and the norm of the acceleration. Like the second method, the system is triggered at the instance both variables exceed their threshold.

The output of an IMU contains a set of many variables. More than one variable might be measuring the same driving principle governing the behavior of the system. To simplify this problem groups of variables are replaced with a single new variable. These are obtained by Principal Component Analysis (PCA), each new variable is described by a principal component. A principal component is a linear combination of the measures, the importance of each measure is expressed in the coefficients also knowns as loadings. The number of principal components that is fed into the classifier can be varied. This algorithm is used to set the parameters and thresholds of the sixth and last method.
4 Experimental Set-up

This section provides a description of the executed experiment. The purpose of the experiment is to collect data by which the fall detection method can be evaluated. Trunk and leg movements were recorded during events in which balance is lost and during activities of daily living (ADL) by means of 3D motion capture (MoCap). Next to the MoCap the characteristics of the movement were measured by an IMU, as described in Section 3.1.1. A schematic overview of the experimental set-up is presented in Figure 5. In this section the experimental set-up is described in detail; the applied apparatus in Section 4.1 and the used protocol in Section 4.2.

Figure 5: Apparatus used in experimental set-up. Three sub sets of the set-up are indicated; Motion Capture by Qualisys system with four camera’s, Challenging Task including the balance board and screen to enable feedback of CoP and Detection system by IMU sensor and required hard- and software to store data.

4.1 Apparatus

A total of 16 participants were recruited of which 10 are male and 6 female, their age is $26 \pm 1.7$ years. None of the participants had health problems related to the ability to maintain balance.

Movement characteristics during the experiment are measured by means of
a IMU, see section 3.1.1. The IMU (sensor) is attached to the trunk via a belt (Figure 7d), to minimize the movement of the sensor with respect to the pelvis. The sensor is connected to the host-PC, via the target-PC, on which all raw and processed data is saved. The sample frequency was set at 1000 Hz and the sensory data is stored in a .mat-file together with a trigger signal.

The motion capture is performed by the Qualisys Track Manager (QTM); this system uses passive markers and a set of four camera’s to obtain 3D trajectories of the body parts. At start and stop of the measurement a trigger is sent to the host PC. This enables the synchronization of the recorded motion capture and the data obtained by the sensor. The data is stored in a .qtm-file, this is exported to a .mat-file, with a sample frequency of 200 Hz.

To track the upper trunk markers are placed on the shoulders, these markers are integrated into a backpack, and on the pelvis, these markers are integrated into a belt. Next to these, markers are placed on the toes (distal head of the first metatarsal) and ankles (lateral malleolus) to capture the movement of the feet. Two markers are placed on the wrists (head of the ulna) to create a possibility to check whether the arms are always in position. One marker is attached to the belt at fixed distance of 6 cm to the IMU (sensor). An overview of the labels (i.e. the names) and location of the markers is given in Table 2. A photographic overview of the front and back of the participant wearing the marker balls can be found in Figure 6.

<table>
<thead>
<tr>
<th>Label</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>RHEE, LHEE</td>
<td>Toes, lateral malleolus**</td>
</tr>
<tr>
<td>RTOE, LTOE</td>
<td>Heels, distal head of the first metatarsal**</td>
</tr>
<tr>
<td>IMU</td>
<td>6cm below the actual IMU (sensor)</td>
</tr>
<tr>
<td>RPEL, LPEL</td>
<td>Hips, at belt around the hips</td>
</tr>
<tr>
<td>RSHO, LSHO</td>
<td>Shoulders, at backpack</td>
</tr>
<tr>
<td>RWRI, LWRI</td>
<td>Wrists, head of the ulna **</td>
</tr>
</tbody>
</table>

Table 2: Marker positions and corresponding labels. **Human anatomical landmark

Figure 6: Actual marker positions; RHEE, RTOE, LTOE, RPEL, LPEL, RWRI LWRI, IMU, RSHO and LSHO
During the experiment the participant stood on board\textsuperscript{*} registering the CoP. The output of the board is shown to the participant on a monitor. The real-time feedback of the balance board is used as input for the challenging task. For the Activities of Daily Living (ADL) a stool is required, see Figure 7b.

4.2 Protocol

This section provides a description of the performed protocol during the experiments. A task is performed in which balance is lost, so called ‘challenge’. The subject is asked to lean to one side as far as possible, eventually a corrective step has to be taken by the subject. Series of ADL are used as condition in which the alarm should not be triggered, to evaluate specificity.

During the task the participant is instructed to keep his arms crossed in front of their body. Markers are attached to the wrists to enable a check whether this is the case. The participant is asked to place the feet in front of each other, toe against heel.

The task is based on the output of the balance board. A laptop runs a matlab file which determines the Center of Pressure (CoP), based on the output of the balance board. An external screen enables the participant to see the current CoP. The position of the CoP is real-time presented to the subject as well as a

\textsuperscript{*}WII balance board, Nintendo Co., Ltd., Kyoto, Japan
target CoP. The subject is instructed to reach the target by change of posture, a corrective movement (step out) should be made rather than not reach the target. As the target is hit it moves in lateral direction to a randomly chosen side, either left or right. As soon as the participant is forced to take a corrective step the target starts from the center. A corrective steps is detected when the participants steps aside the balance board. The further the participant is leaning sideways the more points are earned. This performance measure is used to motivate the subject to lean beyond the position in which he/she is able to maintain balance.

A series of four ADL is executed two times by each subject. In all activities the participant starts and ends in upright standing position. Before the trials are recorded the participant is allowed to familiarize with the activities.

- Sitting down on a stool (height of 40cm) and standing up.
- Bending or squatting down to pick up a small object from the floor, and rising back up.
- Lie down on the side and rising up.
- Wandering around, including some backward steps.
5 Experimental Evaluation - validation

This section describes the methods applied to validate the measurements and the results of that evaluation. The purpose is to gain insight in the data-set and to exclude outliers. The accuracy of both the Motion Capture and the sensor are evaluated. The validity, the correspondence between Motion Capture and the sensor, is also taken into account.

5.1 Methods

The first methods are applied to check the visibility of the markers and accuracy of the Motion Capture (MoCap). Next to these are the methods to check the accuracy of the sensor (IMU). The correspondence between the IMU and the MoCap is checked, regarding lateral lean angle and the norm of the acceleration.

5.1.1 Motion Capture

In the trajectories, recorded by the 3D motion capture, gaps occur. Due to the movement of the body the markers are not visible to the cameras at all times. A trial is excluded if a one of the body parts is not visible for more than 5% of the duration of the recording. A lack of visibility can be compensated for by a marker on the same body part, the feet for example are tracked by both a marker on the heel and the toe. For each marker the fill percentage ($r_{fill}$) is calculated as $r_{fill} = \frac{t_v}{t}$, where $t_v$ equals the time a marker is visible and $t$ is the total duration of the trial. If the fill percentage is below 95% the trial is rejected.

To gain insight in the accuracy of the Motion Capture, the distance between the markers on the backpack is evaluated. Since these markers are at fixed locations the distance should be constant and equal in all measurements. The real distance, measured with a ruler, equals 153 ± 1 mm. For instances at which one or both of the markers is lost, i.e. a gap in the trajectory, the distance cannot be calculated. These instances are therefore discarded. The remainder is used to calculate the mean and standard deviation of the distance between the markers at the backpack.

5.1.2 Accuracy of the sensor

During the static trials the standard deviation of the data captured by the IMU has to be close to zero, since there are only small movements. During the other trials a higher variance is expected since the IMU follows the movements of the participant. The linear acceleration in x-, y- and z-direction has been evaluated for the static trials.
5.1.3 Correspondence between sensor and Motion Capture

The linear acceleration of the lower back is measured by the IMU. And to enable validation this acceleration is also estimated based on the Motion Capture data of the marker placed close to the IMU. This marker is placed at fixed distance of 6cm below the IMU. The IMU and the MoCap respectively measure and track the same variable. To evaluate the validity both signals were compared to each other.

The MoCap provides only information of the marker positions. Since it has to be compared to the acceleration from the IMU, the data is differentiated two times. The orientation of the IMU is not fixed to the coordinate system used for the MoCap. Therefore the norm of the acceleration is evaluated.

The data of the IMU has to be resampled, since the sample rate of the MoCap and the IMU are not equal. Every fifth sample is taken from the data of the IMU. The data is filtered using a second-order low pass Butterworth filter, with a cutoff frequency of 20 Hz for MoCap and 50 Hz for the IMU.

Besides the linear acceleration the lateral lean angle of the upper body is measured by the IMU and estimated based on the Motion Capture (MoCap) data of the shoulder markers. To evaluate the validity of the IMU both signals are compared to each other.

Since it is possible to perform the task with a curved spine, the lean angle at shoulder position is different from the lean angle at the position of the IMU. Therefore the correspondence between the angle measured by the IMU and the angle estimated based on the MoCap data is evaluated instead of the absolute angle.

The correspondence between MoCap and IMU is for both linear acceleration and lean angle evaluated. For every trial the Pearsons linear correlation coefficient ($\rho$) and the probability factor ($p$) are calculated. If $p$ is less than 0.05, the correlation is significantly different from zero and it is likely that a linear correlation exists.

5.2 Results

In this section the results of the validation of the IMU and MoCap are presented. First the results related to the Motion Capture are presented. Thereafter, sensor accuracy and the correspondence between MoCap and IMU are covered. Data that is not within the boundaries, set to exclude outliers, is rejected and not taken into account in the subsequent evaluation step.
5.2.1 Motion Capture

Many gaps in the MoCap trajectories of ADL occur, since the markers are not always visible to the camera system. Mostly, this takes place during the movements in which the participant picks something up from the ground or lies down. The trials of ADL could not be labelled. The Motion Capture data of the ADL are therefore discarded from further analysis. The mean fill percentage per marker during the trials of the challenges are calculated, the result is shown in Figure 8. The markers placed on the left heel are most often not visible. However, since the foot is also captured by a marker on the left toe this did not cause any problems in post-processing the data. The marker located near the IMU is almost all the time visible.

![Figure 8: Mean fill percentage of Motion Capture trajectories per marker. In table 2 the location of each marker can be found.](image)

For all the trials in which the challenging task is performed the shoulder distance is calculated, the distance equals $154 \pm 7$ mm. This is close to the real distance of $153 \pm 1$ mm.
5.2.2 Accuracy of the sensor

The standard deviation of the sensory (IMU) data is calculated for each static trial. The results are shown in Figure 9. The standard deviation is, as expected, close to zero. This supports the reliability of the IMU. Outliers occur for both acceleration in x- and y-direction, these belong to the same participant.

Figure 9: Standard deviation of the acceleration along x-, y- and z-direction. Obtained for each static trial, n=16.

During execution of the experiment by participant number 11 it was noticed that the backpack had physical contact with the sensor. This is the source of high noise levels in the sensory (IMU) data. The data of this participant is therefore not reliable and is discarded from further analysis.

5.2.3 Correspondence between sensor and Motion Capture

There is a significant correlation between the linear acceleration signal of the sensor and the estimated acceleration based on the Motion Capture. For all trials in which the challenge is performed a linear correlation coefficient $\rho$ is found with a probability factor $p < 0.05$. This validates the sensor system, with regard to the norm of the linear acceleration.

A sample of a representative trial in which the challenge is performed is given in Figure 10. As can be seen the characteristics of the lean angle are similar for both the tracking by Motion Capture and the data of the IMU. This observation is supported by the results of the correlation test.

For all trials in which the challenge is performed the correlation of shape is evaluated by means of the Pearsons correlation. For all trials a significant ($p <$
0.05) correlation coefficient is found, this support the correspondence between the data of the IMU and the Motion Capture.

![Figure 10: Lean angle in lateral direction, corrected with mean per signal. MoCap represents the signal obtained by Motion Capture, IMU represents the signal recorded by the sensor.](image)

5.3 Conclusion

The Motion Capture data recorded during ADL are discarded, due to the many gaps in the trajectories. The Motion Capture of the trials in which the challenge is performed can be used, regarding fill percentage. Especially the fill percentage of the IMU is high. This is advantageous, since this marker is used to evaluate the correspondence between MoCap and IMU. The accuracy of the Motion Capture is evaluated based on the distance between the markers at shoulders, the results show a good accuracy: 154 ± 7 mm compared to the real distance of 153 ± 1 mm.

The evaluation of the accuracy of the sensor results in small standard deviations of the acceleration. The only subject of which data is not reliable is number 11, since the backpack had physical contact to the IMU.

At last the correspondence between the IMU and Motion Capture is observed for two variables; the norm of the acceleration and the lateral lean angle. The results show a significant correspondence between sensory (IMU) data and tracking by the Motion Capture. For both variables the correlation coefficient is found to be significant.
6 Experimental Evaluation - classifiers

A reliable trigger for a robotic device is investigated in the section. In Section 6.1 the methods applied to evaluate the classifiers are described. The results of this evaluation are given in Section 6.2. To compare the classifiers the performance for each classifier is expressed in sensitivity and specificity rate. The conclusion is drawn in Section 6.3.

6.1 Methods

The first step is classification of all tracked data into stable and unstable phases. Next the classified data is split into a training- and evaluation set. The data of the training set is used to set the parameters of each method and the classifier is evaluated based on the data of the evaluation set. The performance of all classifiers is compared based on the specificity- and sensitivity rate.

The classification of stable and unstable phases in the trials of the challenge and the partitioning into training- and evaluation sets is the same for all classifiers. After execution of these two steps the thresholds and performance rates are calculated based on the obtained data sets.

6.1.1 Classification based on Motion Capture

The sensory information of the IMU tracked during the challenges is classed either as unstable or as stable. The classification is based on the MoCap data of the feet. An unstable phase is detected at the instance a foot leaves the balance board \((t_1)\). The time interval of the unstable phase is \([t_1 - d_t, t_1]\), where \(d_t = 0.5s\). The time interval of the stable phase is \([t_2 - dt, t_2]\), where \(t_2\) lies 12 seconds \((D_t)\) before \(t_1\). A graphical overview of the described intervals can be found in Figure 11. All instances that are not classed are rejected for further processing. All sensory information of the IMU tracked during Activities of Daily Living is classed as stable, to evaluate the specificity of the classifier.

![Figure 11: Classification method based on Motion Capture. Graphical overview of the intervals.](image-url)
6.1.2 Training- and evaluation set

The data is grouped into a training- and evaluation set according to the sets defined in table 3. One of the two trials of the challenge is randomly selected as training data, the other trial is used as evaluation data.

Fixed subsections of ADL were used for training and evaluation. For training: sitting down, picking up an object from the floor and walking were selected. For evaluation: the trials where the subject lied down were used. To obtain equal size of data tracked during challenge and ADL, the data of the ADL is reduced by randomly picking instances.

<table>
<thead>
<tr>
<th>Training</th>
<th>Evaluation</th>
<th>Remark</th>
</tr>
</thead>
<tbody>
<tr>
<td>Challenge trial 1</td>
<td>Challenge trial 2</td>
<td>Randomly picked which trial is in training set; the other used as evaluation</td>
</tr>
<tr>
<td>ADL: Sit down, pick something up on the floor and walking</td>
<td>ADL: Lie down</td>
<td>Reduced size by randomly picking instances</td>
</tr>
</tbody>
</table>

Table 3: Data of the trials in which the challenge is performed and of the trials of ADL are grouped into a training- and evaluation set.

6.1.3 Set the parameters of the classifiers

In Section 3.3 a set of classifiers is proposed. For some of the classifiers it is required to pre-process the data, for example the calculation of the norm of the acceleration. The following lists the classifiers and their points of interest.

- **$a_{\text{norm}}$:** The norm of the acceleration is used as single variable to trigger the system. The norm of the acceleration is calculated from the raw data, $a_{\text{norm}} = \sqrt{x^2 + y^2 + z^2}$.
- **$a_{\text{combi}}$:** A combination of the horizontal acceleration and vertical acceleration is used to trigger the system. At the instance both variables exceed their threshold the system detects a fall. The horizontal acceleration is calculated form the raw data, $a_{\text{hor}} = \sqrt{x^2 + y^2}$.
- **$\alpha_{\text{lean}}$:** The lean angle in lateral direction is used as single variable to trigger the system.
- **$\dot{\alpha}_{\text{lean}}$:** The angular velocity in lateral direction is used as single variable to trigger the system.
- **$a_{\text{combi-2}}$:** The data of the lean angle $\alpha_{\text{lean}}$ and the norm of the acceleration $a_{\text{norm}}$ are used as combined threshold.
- **PCA:** The data is transformed into principal components, a principal component is a linear combination of the variables. The number of principal components that is fed into the classifier is varied.
For each method except PCA, the thresholds are set based on the data of the training set. Since the variation between subjects is expected to be high, the classifiers are trained on an intra-subject basis. The performance, expressed in specificity and sensitivity, is calculated as a function of the threshold. The threshold is selected at the Equal Error Rate (EER), the specificity and sensitivity rate are equal for that value. This is chosen to obtain both high rate for specificity and sensitivity, instead of high performance rate for one of them. The graph in Figure 12 shows the expected curves for specificity and sensitivity.

Figure 12: Expected curves for performance rates over threshold; sensitivity and specificity. The selected threshold is at the value of the Equal Error Rate (EER)

6.1.4 Evaluation of the classifiers

The determined threshold of the classifier is used to evaluate the classifiers. The performance rates, sensitivity and specificity, are calculated based on the data from the evaluation set. For the PCA-method the coefficients of the principal components that are determined during training are also used in the evaluation. The data of the evaluation set is transformed, with these coefficients, to match the principal components of the data of the training set.

6.2 Results

This section gives the results of the methods applied to set the parameters of the classifiers. And the actual results of the classifier itself regarding performance rates. The structure is the same as the section in which the methods are described.
6.2.1 Classification based on Motion Capture

All data of the trials in which the challenge is performed is classified. The result of a single step as performed by participant number 2 is shown in Figure 13. The unstable phase matches the instance a step is taken by the left foot. During the stable phase the feet do not move in lateral direction.

![Classification over time](image1)

**Lateral position [mm]**

**Time [s]**

**Lateral direction of the feet − MoCap**

LHEE

RHEE

Stable

Unstable

![Lateral position vs. Time](image2)

**Figure 13**: Characteristic result of classification based on Motion Capture of a single step, by participant number 2. LHEE and RHEE represent the marker on the left and right heel respectively.

6.2.2 Training- and evaluation set

The classifier is per participant trained and evaluated with the complete set of data, grouped as the method describes. Besides using all the pool data, the classifier is trained and evaluated just with the data of the trials of the challenges, this represents a more controlled environment.
6.2.3 Set the parameters of the classifiers

For every participant the threshold(s) for each method is set. The graph in Figure 14 shows the performance rates dependent on the threshold of the lean angle for participant number 6. The best threshold is chosen at value of EER.

The interval for which the threshold is calculated differs per classifier. The range of thresholds is estimated empirically.

![Figure 14: Characteristic result of performance rates over threshold for lean angle, based on results of participant number 6.](image-url)
The obtained values of the thresholds for all participants are presented in Figure 15. The thresholds of the classifiers that use a combination of two different variables are presented together. The obtained values for the combination of lean angle ($\alpha_{\text{lean}}$) and norm of acceleration ($a_{\text{norm}}$) are lower than the values obtained for the values obtained if those variables are applied individually.

The obtained threshold for the $a_{\text{norm}}$, approximately $2.5 \text{ m/s}^2$, lies below the thresholds presented in earlier studies which equals approximately $5 \text{ m/s}^2$. The lateral recovery angle presented by Carbonneau (2013) is larger, $0.17 \text{ rad}$ versus the obtained threshold of $0.07 \text{ rad}$.

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6.2.4 Evaluation of the classifiers

Each boxplot presented in this section provides a result of the group of participants, $n = 15$. Figures 16 - 21 give an overview of the results obtained for each classifier, based on the complete training- and evaluation set. For each classifier the results show during training an equal specificity and sensitivity rate, which is expected because of the application of Equal Error Rate. The following abbreviations are used:

- $Spec_{\text{train}}$ represents the specificity rate obtained for the training set
- $Sens_{\text{train}}$ represents the sensitivity rate obtained for the training set
- $Spec_{\text{eval}}$ represents the specificity rate obtained for the evaluation set
- $Sens_{\text{eval}}$ represents the sensitivity rate obtained for the evaluation set

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Figure 15: Obtained values for the threshold(s) of all classifiers.
The mean value of the EER during training equals 0.65 ± 0.12, as presented in Figure 16. In the evaluation the specificity performance decreases, whereas the sensitivity is maintained. The standard deviation of the sensitivity is higher in the evaluation than during training.

![Figure 16: Results of the $a_{\text{norm}}$ threshold.](image)

The results of the classifier based on the combination of vertical and horizontal velocity are given in Figure 17. The classifier achieves a mean EER of 0.59 ± 0.10 in training. In the results of the evaluation an increase of specificity occurs, at the expense of sensitivity.

![Figure 17: Results of the $a_{\text{combi}}$ threshold.](image)
In Figure 18 the results of the $\alpha_{\text{lean}}$ classifier are presented. The threshold used in the classifier based on the lean angle equals 0.07 rad. The mean performance rate is $0.66 \pm 0.06$ in training. The evaluation shows a decrease of sensitivity and an increase of specificity.

![Figure 18: Results of the $\alpha_{\text{lean}}$ threshold.](image1)

The result of the $\dot{\alpha}_{\text{lean}}$ classifier equals $0.62 \pm 0.18$. The specificity is maintained in training, the sensitivity however has dropped to $0.20 \pm 0.10$. As can be seen in Figure 19.

![Figure 19: Results of the $\dot{\alpha}_{\text{lean}}$ threshold.](image2)
The result of the combined classifier of $a_{\text{norm}}$ and $\alpha_{\text{lean}}$ is presented in Figure 20. The EER equals $0.68 \pm 0.10$ in training. This is the highest performance of the classifiers based on a threshold for one or two variables.

Figure 20: Results of the combined threshold classifier of $a_{\text{norm}}$ and $\alpha_{\text{lean}}$. 

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The results of the PCA looks different, since there is no threshold to be compared. Instead the effect of the number of principal components is shown in Figure 21.

Table 4 gives an overview of the obtained results.

<table>
<thead>
<tr>
<th>Rate</th>
<th>$\alpha_{\text{norm}}$</th>
<th>$\alpha_{\text{combi}}$</th>
<th>$\alpha_{\text{lean}}$</th>
<th>$\alpha_{\text{combi}2}$</th>
<th>$\alpha_{\text{lean}}$</th>
<th>PCA(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specificity - training</td>
<td>.66 ± .11</td>
<td>.59 ± .11</td>
<td>.67 ± .06</td>
<td>.68 ± 0.10</td>
<td>.61 ± .19</td>
<td>.85 ± .20</td>
</tr>
<tr>
<td>Sensitivity - training</td>
<td>.65 ± .13</td>
<td>.59 ± .10</td>
<td>.66 ± .06</td>
<td>.68 ± 0.10</td>
<td>.63 ± .18</td>
<td>.60 ± .22</td>
</tr>
<tr>
<td>Specificity - evaluation</td>
<td>.40 ± .11</td>
<td>.94 ± .07</td>
<td>.81 ± .06</td>
<td>.30 ± 0.25</td>
<td>.71 ± .12</td>
<td>.80 ± .20</td>
</tr>
<tr>
<td>Sensitivity - evaluation</td>
<td>.63 ± .26</td>
<td>.01 ± .01</td>
<td>.31 ± .07</td>
<td>.68 ± 0.37</td>
<td>.20 ± .10</td>
<td>.17 ± .28</td>
</tr>
</tbody>
</table>

Table 4: Performance rates for all methods, PCA with two principal components.
Figure 22 shows the performance rate of the $\alpha_{\text{lean}}$ classifier based on just the data of the trials of the challenges. The data of the ADL is not taken into account to train and evaluate the classifier, so both training and evaluation are in a more controlled environment. The results show high specificity and sensitivity in both training and evaluation.

![Graph showing performance rate vs. threshold lean angle]

Figure 22: Results of the $\alpha_{\text{lean}}$ method based on only the trials in which the challenge is performed.
To evaluate inter-subject variability for each classifier the obtained thresholds are averaged over the participants. The mean threshold is applied to the training set, to gain insight in the affect. The standard deviation in performance rate increases significantly for all classifiers, except for the classifier based on the lean angle. The combination of horizontal and vertical velocity result in the largest difference in performance rates. The results are given in Figure 23.

![Figure 23](image)

Figure 23: Results to gain insight in inter-subject variability

### 6.3 Conclusion

The classification based on Motion Capture and the partitioning into training- and evaluation sets is performed as proposed. No overlay of stable and unstable phases or other issues did occur. The obtained thresholds differ from the reported values in earlier studies. The results of the evaluation of inter-subject variability support the ability to generalize the found thresholds over participants.

To pick the best classifier all methods are compared based on their specificity- and sensitivity rates for the data of both the training- and evaluation set. The training results in performance rates at EER of maximal 0.68 ± 0.10, this is not at high as desirable. However the results of the evaluation are even lower, either the specificity or sensitivity drops to a value of maximal 0.40 ± 0.11. For the classifiers $a_{\text{combi}}$, $\alpha_{\text{lean}}$, $\dot{\alpha}_{\text{lean}}$ and $PCA(2)$ the specificity in evaluation is high, at cost of a low sensitivity rate. For the other classifiers $a_{\text{norm}}$ and $a_{\text{combi2}}$ the sensitivity is high, at cost of a low specificity.
7 Conclusion

This study is part of the MARS\textsuperscript{3} project*. The purpose of that project is to improve balance control and reduce risk of falls by means of a robotic assistive system. Development of a balance assistive device, which is based on a gyroscopic control output, is the ultimate goal of the coordinating project.

In this study a reliable trigger, based on the measured signals of the sensor system, for a robotic device is investigated. The validity of the proposed sensor system, which is implementable into the robotic device, is evaluated by means of a comparison between sensor output and estimations based on 3D-motion capture of the subject.

The trajectories, recorded by the Motion Capture, of the trials in which the challenge is performed are evaluated regarding fill percentage and accuracy; the results of these evaluations are good. The sensory information (IMU) is for all subjects, except number 11, within the limits of accuracy. The evaluation of the correspondence between Motion Capture and IMU is significant ($p < 0.05$) for both the linear acceleration and the lateral lean angle.

Although the sensory information is in correspondence with the actual body movement, the proposed classifiers do all result in sensitivity and specificity rates that are not high enough to implement the classifier into an assistive device. The value of information is too low, it is not possible to distinguish \textit{stable} and \textit{unstable} phases by means of the proposed classifiers.

\footnote{Machines Assisting Recovery from Stroke and Spinal Cord Injury for reintegration into Society - Rehabilitation Institute of Chicago (RIC)}
8 Discussion

This section discusses the results of the steps taken to design the six proposed classifiers.

The first step of classification is the determination of the steps, this is based on the lateral position of the feet. The risk of this method is overlay in the stable and unstable classes; at the moment a participant is taking corrective steps with a small time duration in between. There is no observation that this overlay exists in the classed data.

The training- and evaluation sets are fixed. It might be possible that another arrangement results in other threshold values and performance rates.

The range of parameters for each threshold is determined empirically. The results show that most of the participant fit within these thresholds, a maximum of three outliers is observed. The applied threshold in earlier studies are all higher than the results obtained in this study, it is likely due to the difference between detection of a fall event and loss-of-balance.

Since the performance rates are low, there is not been looked into other criteria to evaluate the classifier, such as ‘lead-time’.

All participants were young adults. This constraints the results. It is not likely that the obtained thresholds are suitable for the device used by elderly.
9 Recommendations

This section provides some recommendations and side issues related to an assistive device. The Human Machine Interaction covers the adaptation of the user to a device and the human response to applied support. These issues are described in Section 9.1. The importance to fit the classifier to the task is discussed in Section 9.2.

9.1 Human Machine Interaction

When a function is completely and permanently taken over by an automated system the function will be seen as a machine operation. The behavior and performance of humans is adapted to this technical process. The skills of the human operator are adapted to the available amount of automation, this may induce loss of skills. This adaptive process is described in detail by Endsley (1999) [27].

The support has to be based on the outcome of the sensor system and also on the human response to an applied torque. The human response to a perturbation generated by the torque of the flywheel has not been evaluated so far. To gain insight in the human response it is recommended to evaluate this response in an additional study.

9.2 Fit to the task

For an hip protector specificity is more important than for a system which gives continuous support. By means of an airbag device which activates at the moment a fall is detected. For a hip protector it is harmful if specificity is not 1, a false alarm causes damage. With continuous support it is no problem if specificity is not 1, since it does not cause any damage if support is applied when not required.

There are a lot of differences in movement patterns for different humans. It might be valuable to set up an algorithm in which the normal movements of a human are used to settle certain thresholds and optimize the algorithm for that specific user. One could use ADL to obtain the required movement characteristics. Note that this is not in congruence with the obtained results in this study, the inter-subject-variability is not high according to the classifiers.
10 Acknowledgements

One and a half year ago I was introduced to the MARS project. I started my internship in Twente and did my first experiments regarding balance control. The experience in the lab was really good and motivated me to continue working on the project.

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