Alma Mater Studiorum – Università di Bologna

DOTTORATO DI RICERCA IN

BIOINGEGNERIA

Ciclo XXIV

Settore Concorsuale di afferenza: **09/G2 - BIOINGEGNERIA**

Settore Scientifico disciplinare: **ING-INF/06 - BIOINGEGNERIA ELETTRONICA E INFORMATICA**

ASSESSMENT OF DAILY LIFE MOBILITY LEVELS USING WEARABLE INERTIAL SENSORS AND MINIMUM MEASURED INPUT MODELS

Presentata da: **Alper KÖSE**

Coordinatore Dottorato **Relatore**

Prof. Angelo CAPPELLO **Prof. Ugo DELLA CROCE**

Esame finale anno 2012

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CHAPTER 1

INTRODUCTION

Human movement is a complex phenomenon with many contributing factors: physiology, mechanics, psychology, etc. An ability to assess the quality or quantity of movement has the potential to provide an invaluable source of knowledge to clinicians to accurately diagnose and treat a variety of medical conditions [1]. Assessing the mobility level of individuals during daily life is essential for complementing the information gathered in confined environments such as clinical and physical activity laboratories for the assessment of mobility. A better understanding on people's real life may be possible if their physical activity is monitored during a typical day to provide an estimate of their mobility level, thus, increasing the impact of training programs or clinical interventions.

Movement analysis under controlled environment is a useful tool, but does not reveal functional subject variability in everyday activity patterns. A patient's level of mobility cannot be reliably estimated from the quality of movement. The quantity of movement in daily life should also be measured [2].

To acquire needed data during daily life, wearable devices provide very good solution. Complicated wearable systems such as garments with embedded sensors are designed as an undershirt with various sensors embedded within them. Data are transmitted to a pager-size device attached to the waist portion of the shirt where it is sent via a wireless gateway to the Internet and routed to a data server where the actual monitoring occurs. Optical fibers, a data bus, a microphone, other sensors, and a multifunction processor, all embedded in a basic textile grid [3].

Inertial measurement units (IMUs) are used as a subset of wearable devices to monitor the motion of human movement [1]. They are used to measure applied acceleration and angular velocity along and around a defined axis. The availability of commercial small and light-weighted wearable modules with an extended battery life allows for monitoring human movement for prolonged periods of time and without space limitations. IMUs can be used as a stand alone device or a combination of sensors placed on various parts of the body of the subject.

There are various studies reported in literature for long-time monitoring of daily life activities. Some of those studies used multiple sensors placed on various parts of the body [4, 5, 6]. The use of multiple sensors enables more parameters to be extracted from the data acquired; however, since multiple sensors are being used the cost of the systems, the complexities of the algorithms, the memory space required for a long term monitoring increased and also the system might create uneasiness for the subject. In the literature there are studies that use a single sensor to provide an unobtrusive, low-cost and less-complex solution [7, 8, 9].

1.1 Research Objectives

Our research started as a part of a PRIN’07 project (PI Prof. Della Croce). Its main goal was the evaluation of the mobility of healthy individuals living in an urban context in relation with fitness level, age and gender. Our research was focused on the biomedical engineering portion of the project. Main tasks were related to inertial sensor data enhancement for detection and classification of activities, and, analysis and interpretation of enhanced data. Our research was continued, focusing on extracting parameters from the sensor data for specific activities such as gait. We developed an algorithm that extracts temporal parameters and estimates the spatial parameters of gait.

1.2 Material and Methods

Single IMU (FreeSense, Sensorize®) (Figure 1.1) featuring a tri-axial accelerometer and two bi-axial gyroscopes (acceleration resolution 0.0096 m/s2, angular rate resolution 0.2441 deg/s, unit weight 93g, unit size 85mm×49mm×21mm) is being used for data acquisition.

Figure 1.1 – IMU Used

For validation purposes of the developed algorithms a commercial device a commercial physical activity assessment device (IDEEA, Minisun®) [4], two stereo photogrammetric systems (BTS SMART-D and VICON MX) and footswitches (BTS FREE EMG) were used for various experiments that will be explained.

1.3 Organization of the thesis

Chapter 2 introduces the technology of sensor that were used during research

Chapter 3 presents the previous studies in literature

Chapter 4 presents the developed method for monitoring of daily life activities

Chapter 5 presents the developed methods for extracting temporal parameters from the sensor data, and also the method for estimation of spatial parameters using the extracted temporal parameters and a specifially designed integration algorithm.

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CHAPTER 2

TECHNOLOGY

2.1 Introduction

Using inertial and magnetic sensors for body tracking is a relatively new technology. They are independent of an artificially generated source (i.e. sourceless), so they are free from range limitations seen in cameras (e.g. Kinetic sensor has a ranging limit of 1.2–3.5 m, similarly, most 3-D sensors operate in well-calibrated distances) and interference problems (e.g. illumination effects).

Low-cost, small size microelectro-mechanical systems (MEMS) sensors are used in the production of wrist-watch-sized inertial/magnetic sensor modules, which make it possible to track orientation in real-time. Also, placing these sensor modules to each of the major limb segments of human body makes it possible to independently estimate the orientation of each segment relative to an earth-fixed reference frame. It is also possible to compile the human model from these independent limb segments without knowing their relative orientation [1].

Inertial measurement units generally consist of three different sensors: accelerometers, gyroscopes and magnetometers. Their descriptions and application areas are briefly explained in the following sections.

2.2 Accelerometers

Accelerometers are devices which measure the applied acceleration along an axis. Although there exist different transducers for this purpose (piezoelectric crystals, piezoresistive sensors, servo force balance transducers, electronic piezoelectronic sensors, etc.), the main theory behind the accelerometers is a spring mass system. The response of the small mass within the system (a force to the spring) is used in order to calculate the applied acceleration.

Using accelerometers provides a practical and low-cost method for monitoring human movements. They are used to measure physical activity levels, for movement identification and classification, and to monitor movements such as gait, sit-to-stand, postural sways and falls.

A uni-axial accelerometer records accelerations in a single direction, while a triaxial accelerometer operates on three orthogonal axes and provides the measurements on each axis. To measure body parts, accelerometers are placed on the body part whose movement is being studied. To measure whole body movements, multiple instruments are used [2].

Activity recognition from accelerometer data is a very active topic in research. In the study of Bao and Intille [3], subjects wear 5 bi-axial accelerometers on different body parts while performing activities such as walking, sitting, standing still, bicycling etc. Data extracted from accelerometers are used in order to train a set of classifiers to discriminate between types of activities [4]. The fact that most modern mobile phones are equipped with accelerometers creates new application drives.

2.3 Gyroscopes

Gyroscope is a device consisting of a vibrating element merged with a sensing element, functioning as a Coriolis sensor. Coriolis effect is an evident force that manifests itself in a rotating reference frame and it is proportional to the angular rate of rotation.

The gyroscope provides angular velocity measurements. Joint angles are derived by the integration of angular velocity, but data obtained can be distorted by offsets and drifts. Alternatively, gyroscopes are used to measure angular velocity without being affected by gravity and linear acceleration.

Their low current consumption makes gyroscopes appropriate for ambulatory monitoring. Aminian et al. propose such a system for the estimation of spatio-temporal parameters during long periods of walking. The values of gait parameters are computed from the angular velocity of lower limbs by using wavelet transform. The validation of measurements was assessed using foot pressure sensors as standard information and data were gathered from young and elderly subjects to calculate the accuracy of the proposed system in a broad range for each gait parameter. The proposed method seems to be a significant monitoring tool for several reasons. First, it enables measurements of gait features during a long period of walking which supplies the stride-to-stride variability of gait. The portability of the system makes it possible to be used in other settings than a gait laboratory, and to obtain information reflecting the real performance of the subjects [5].

Tong and Granat investigate the usage of uni-axial gyroscopes to develop a basic portable gait analysis system. Gyroscopes are attached on the shank and thigh segments' skin surface and the angular velocity for each segment is recorded. Using the segment angular velocities, segment inclinations and knee angle are derived [6].

2.4 Magnetometers

Magnetometer is a device which measures the strength and direction of the magnetic field in its locality. In general, magnetometers are combined with accelerometers and gyroscopes in biomechanics applications to increase the reliability of the system and to make the definition in the global reference frame possible. To do so, they are integrated into Magnetic, Angular Rate and Gravity (MARG) sensor modules.

Bachmann et al. design a MARG sensor module in order to measure the 3 degrees of freedom orientations in real time without singularities (singularity - if the external earth magnetic field is in alignment with any of the sensor axes, the rotation rate about that axis cannot be determined). Each MARG sensor module contains orthogonally mounted micro-machined rate sensors, accelerometers and magnetometers for a total of nine sensor components. The MARG sensor requirements are derived from the necessities of human body motion tracking. The design goal behind MARG sensor is being able to measure 3 degrees of freedom rotational motions without singularities, to be sourceless (not depending on a generated signal source) and to have a suitable form factor, which does not encumber a human subject when the sensor units are attached.

Design and implementation of MARG sensors demonstrate that all sensor components are linear within the intended operating conditions. Besides being used in human body tracking, these sensor units have important applications to teleoperation, virtual reality and entertainment as well [7].

Marins et al. present an extended Kalman filter for real-time estimation of rigid body orientation using MARG sensors. The filter represents rotations using quaternions rather than Euler angles, which eliminates the singularities. A process model is defined, where angular rates are converted into quaternion rates. The Gauss-Newton algorithm is used to find the best quaternion that relates the accelerations and the earth’s magnetic field, which is then used as part of the measurements for matching Kalman filter equations linear. The linearity of the Kalman filter reduces the computational time and the orientation estimation is assessed in real-time [8].

Yun and Bachmann also design a quaternion-based Kalman filter by preprocessing the accelerometer and magnetometer data using the single-frame QUaternion ESTimator (QUEST) algorithm [9]. QUEST represents the positioning of a rigid body relative to a fixed coordinate system. The quaternion produced by the QUEST algorithm is provided as input to the Kalman filter along with angular rate data. When compared with previous approaches, this preprocessing step significantly reduces the complexity of the filter design. Filter performance is validated in experiments and the results are very promising. Even when there are delays, the algorithm manages to handle the dynamic errors [1].

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CHAPTER 3

LITERATURE REVIEW

There are various methods presented in the literature that uses inertial measurement units (IMUs) for acquiring human movement. IMUs can be used with various other sensors such as ECG, EMG, blood pressure sensors etc. Significant progress in computer technologies, solid-state micro sensors, and telecommunication has advanced the possibilities for individual health monitoring systems. A variety of compact wearable sensors are available today and it is expected that more will be available in the near future. This technology is bound to soon allow researchers and clinicians to unobtrusively monitor individuals for extended periods of time in the home and community settings [bonato]

IMUs are suited to be used for human movement analysis, since they can acquire acceleration and angular rate of change and this could be used to estimate displacement and orientation for each segment that they are attached to. The studies that use IMUs can be classified into two groups regarding their use of sensors: multiple sensors and single sensors.

3.1 Multiple IMUs for activity classification

Placing multiple IMUs on various parts of the body allows gathering complex data about specific parts of the body. With multiple IMUs it is convenient to place a sensor in each conjoint segment and estimate the joint kinematics using the acquired data.

Tapia et.al used five IMUs with a hearth rate monitor to classify the activities of daily life. The IMUs locations were: top of the dominant wrist just behind the wrist joint, side of the dominant ankle just above the ankle joint, outside part of the dominant upper arm just below the shoulder joint, on the upper part of the dominant thigh, and on the dominant hip. They have analyzed the 15 acceleration signals (x, y and z components of each) with a sliding window (window length 4.2s and overlapping on 2.1s). Time domain and frequency domain features were then computed for each window: the area under curve (AUC) and variance to capture signal variability, mean distances between axes and mean to capture sensor orientation with respect to ground for postures, entropy to differentiate activity type, correlation coefficients to capture simultaneous motion of limbs, and FFT peaks and energy to discriminate between intensities. All the features were computed over each acceleration axis. The only feature computed over the HR data was the number of heart beats above the resting HR value (BPM-RHR). Finally, WEKA toolkit [WEKA] was used to evaluate the performance of the C4.5 DT [WEKA C4.5] (pruned) and the Naive Bayes classifier. They reached 96% performance for recognition of activities (Lying, sitting, walking, running, stair ascend/descend, cycling, rowing, moving weight, arm exercises). [Tapia+Intille]

Ermes et al. used 2 IMUs placed on wrist and hip to classify daily life activities. For the wrist they have used 3-axial accelerometer and for the hip 3-axial accelerometer and magnetometer. Twelve subjects participated in their studies and 6h of data were collected for each subject. The classified activities were: Lying, sitting (computer work, reading), standing, cycling, rowing exercise, walking (regular and Nordic), playing football, running. They have used various classifiers (decision trees, artificial neural network, hybrid model) and reached 89 % recognition rate.

Paraschiv-Ionescu et al. used 3 IMUs placed on chest, thigh and shank of the subject. The classified activities were standing (with various postures), sitting, lying and walking. They have used wavelet transform and Savitzky–Golay filters for extracting information from the signals and developed different algorithms for each kind of activity. They also used the same setup for extracting gait parameters. They have reached 98% percent recognition rate. They also estimated distance traversed with 6.8% error rate and speed with 9.6 % error rate.

There are also commercial products that use multiple sensors to provide activity classification and gait analysis. Zhang et al. presented this commercial product in their publication. They use 5 IMUs placed on both thigh, under the both foot and on chest. They classified 32 activities and claim to reach 98.7% rate for 32 activities. They provide a profiling of the subject for the daily activities performed. They also provide estimations of gait speed, distance, cadence and other spatio-temporal parameters along with estimations of energy and power.

3.2 Single IMUs for activity classification

In the study of Ravi et al., they used a single IMU for activity classification. They have placed the IMU ın waist level at the right side of the body. Their study was mostly based on the comparison of various machine learning methods applied on activity classification. They have classified following activities: standing, walking, running, ascending/descending stairs, sit-to-stand and stand-to-sit, vacuuming and brushing teeth. They extracted the following features from the IMU signals by analyzing the signals with the sliding window approach: (a) mean value, (b) standard deviation of the signal in each window, (c) energy, which is the sum of the squared discrete FFT component magnitudes of the signal (The sum was divided by the window length for normalization), and (d) correlation between the signals in each window. They used various classifiers but the most prominent one was the method called plurality voting that uses all the other classifiers for making a decision with 90% to 99% recognition rate in various cases.

Yang et al. proposed a method that uses a single IMU placed on the dominant wrist of the subject. They have divided the activities into two groups: (a) static and (b) dynamic. They developed their method using neural classifiers with multilayer feed-forward neural networks architecture. They trained two different neural classifiers: First one is for classifying the activity as dynamic or static and second one classifies the output from the first classifier. They analyzed the signal using the same approach of Ravi et al., however, they extracted additional features from the signal. The additional features are: interquartile ranges, root mean square, mean absolute deviation and variance. The classified activities were: standing, sitting, walking, running, vacuuming, scrubbing, brushing teeth, and working at a computer. Seven healthy subjects participated in the experiments performing each activity for 2 minutes. They have reached 95% recognition rate.

Mathie et al. proposed a method with a single IMU placed at waist level above the fight anterior superior iliac spine. The movements were first divided into activity and rest. The activities were classified as falls, walking, transition between postural orientations, or other movement. The postural orientations during rest were classified as sitting, standing or lying. In controlled laboratory studies in which 26 normal, healthy subjects carried out a set of basic movements, the sensitivity of every classification exceeded 87%, and the specificity exceeded 94%; the overall accuracy of the system, measured as the number of correct classifications across all levels of the hierarchy, was a sensitivity of 97.7% and a specificity of 98.7%.

Najafi et al. proposed a method using a single IMU attached to the chest. Wavelet transform, in conjunction with a simple kinematics model, was used to detect different postural transitions (PTs) and walking periods during daily physical activity. They developed different methods for detecting lying, sitting and standing, and walking. They classified activities using the outcomes of these different methods. They reached 92% to 99% recognition rate with 90% to 98% sensitivity.

3.3 Multiple IMUs for gait analysis

Tong and Granat [10] presented their study in 1999 using uniaxial gyroscopes. The IMUs were placed on thigh and shank. They used the first five seconds of the acquisitions where the subject stands still to remove the drift from the signal. After they subtract the offset value from the static part of the acquisition, they applied simple integration to estimate the inclination of the segment. The gait event detection was done by using footswitches and they proposed that the step length can be calculated using the leg length of the subject and the inclination calculated from the IMU on the shank.

Aminian et al. [11] worked on spatio-temporal parameters of gait using multiple gyroscopes. They have used three gyroscopes placed on each shank and on the right thigh. A wavelet based method was developed to estimate the heel strikes and toe-off events. The method for the estimation of gait events used the signals from the IMUs attached to the shanks. Each sensor was used to estimate gait events for the relevant foot. Temporal parameters of the gait were estimated using the gait events. For the spatial parameters, a pendulum model was developed. In this model the swing phase was modelled as a double pendulum model, while the stance phase was modelled as the inverse double pendulum model. They measured the length of the thigh and shank before the acquisitions and used this information together with the amount of rotation estimated from the signals of right thigh and shank as the required parameters for the double pendulum model. The root mean squared difference of temporal parameters were 23ms for right swing time, 8ms for gait cycle time. They found out that the heel strike detection method was overestimating the event by 10ms in average, relative to the footswitches [11]. In a later study they have applied their method for spatio-temporal parameters estimation on clinical patients with hip osteoarthritis after total hip replacement [12].

Takeda et al [13, 14] proposed a setup where seven IMUs were used. The IMUs were placed on abdomen, left and right thigh, left and right shank and left and right foot. In their first study [13], they developed a wavelet based method to estimate the inclination of the sensor and using the inclination they estimated the flexion of hip and knee. In their second study [14] they focused on gait analysis using all the sensors. They measured the distance of the sensors on the thigh and shank from hip, join and knee joints. They used this information along with the inclination to estimate both hip, knee and ankle joint angles. Also they proposed a model to create a stick figure of lower limbs with their setup.

3.4 Single IMU for gait analysis

Zijlstra and Hof [15] worked on the feasibility of an analysis of spatio-temporal gait parameters based upon accelerometry. Their setup was using only one IMU placed in the back of the subject at the waist level. 25 healthy subjects participated in the study. 15 of them walked on a treadmill that was equipped with force transducers underneath a left and a right walking surface and the rest walked overground. A pendulum model was developed based on a previous study [16]. Based on this model, they estimated the foot contact event as the zero-crossing point on forward acceleration where the switch from positive to negative occurs. They also proposed a refinement method where the peak before the zero-crossing was estimated as foot contact point. The discrimination between left and right steps was based on the analysis of medio-lateral movement of the pelvis. The developed inverted pendulum model states that the center of mass (CoM) accelerates to the left during right support phase and to the right during left support phase. In the proposed method position of the CoM was chosen as the discriminator between left and right step. A Butterworth filter with 0.1 Hz cut-off frequency was applied to reduce the effect of the drift and the first harmonic was used to describe amplitude and timing of the left/right displacement pattern during a stride cycle. The estimation of step length was based on the relations between the changes in height of CoM and step length [16]. They developed a formula to estimate step length using the changes in height of CoM given the leg length of the subject. A Butterworth filter with 0.1 Hz cut-off frequency was applied on the vertical acceleration to reduce the effect of the drift and the displacement was estimated by double integration. The amplitude of the displacement was used to estimate the step length. They reported that peak detection method was giving better and stable results than zero crossing method for the detection of foot contacts. However, in their method, left and right foot contacts identification failed in some cases where the medio-lateral displacement was small, also the step lengths were underestimated in all subjects and at all speeds. It is presented in the study that the step length underestimation was consistent with all the subjects therefore a multiplication constant of 1.25 was introduced to compensate for the underestimation.

Sabatini et al. [17] proposed a setup with a single IMU placed on the instep of the right foot. The IMU was composed of one biaxial accelerometer and one rate gyroscope. Gyroscope acquired angular velocity in sagittal plane. Angular velocity was integrated starting from each heel-off and orientation of the foot in sagittal plane was estimated. The knowledge of the orientation was used to remove the gravitational contribution from the accelerometer signal. The gait events were detected using the angular velocity. Heel-off after the stance phase occurs when a given threshold (30 deg/ sec) exceeded. The foot take-off detected at the time instant when the angular velocity reaches the maximum value in the clockwise direction. During the swing phase angular velocity is in counter-clockwise direction. The heel strike detected at the time when the angular velocity reaches the maximum value in the clockwise direction for the second time in the gait cycle. The final transition when the foot becomes flat on the ground is detected at the time when the angular velocity slow down to a given threshold value (30 deg/ sec). The phase where the foot is flat on the surface, the foot was assumed motionless. This phase was used as a reference point for the reset mechanism of the double integration of accelerometer signal. They reported that the method tends to detect the toe-off earlier (on average: 35 ms), whilst the heel strike is detected without any systematic difference (on average: 2 ms).

Ojeda et al. [18] presented a study where they used a similar setup with Sabatini et al. [17] The IMU was placed on the lateral side foot. A zero velocity update method, similar to Sabatini et al. was used. The stance phase was detected applying a threshold on the root of squared sum of angular velocity components. In combination with the zero update method, a proposed method of Titerton and Westaon [19] was used to estimate the position of the sensor and the foot. The prosed method was able to estimate the direction and the distance of the sensor. Experiments were made on straight-line, 2-D closed-loop, simple 3-D closed-loop, complex 3-D closed-loop experiments and in longer durations. The errors for the straight line were in average 0.8% for fast and 0.3% for slow speeds. 0.9% error was reported for the simle 2-D closed loop track, 1.7% error was reported for the simle 3-D loop and 0.49% horizontal, 1.2% vertical error was reported for the complex 3-D closed loop experiments. For the longer duration experiments outside location with a rocky terrain was chosen and 2.1% horizontal and 1.9% vertical errors were reported.

Yun et al. [20] proposed a similar method with the same setup presented in the method by Sabatini et al. [17]. In this study an IMU with magnetometer was used. Acceleration, angular velocity and magnetometer signals were used with a Kalman filter to estimate the orientation of the sensor. Also a zero velocity update method was used to correct the drift effect in integration. In this study, stance phase was detected using the vertical accelerometer signal. 1.3% error rate was reported for 120 meter straight line walking and 4.3% error for 120 meter straight line running. 1.8% error rate was reported for 2-D closed loop track with combined forward walking, side stepping, and backward walking

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CHAPTER 4

A SINGLE IMU FOR ACTIVITY MONITORING

4.1 Introduction

Human movement is a complex phenomenon with many contributing factors: physiology, mechanics, psychology, etc. An ability to assess the quality or quantity of movement has the potential to provide an invaluable source of knowledge to clinicians to accurately diagnose and treat a variety of medical conditions [1]. Assessing the mobility level of individuals during daily life is essential for complementing the information gathered in confined environments such as clinical and physical activity laboratories for the assessment of mobility. A better understanding on people's real life may be possible if their physical activity is monitored during a typical day to provide an estimate of their mobility level, thus, increasing the impact of training programs or clinical interventions.

Movement analysis under controlled environment is a useful tool, but does not reveal functional subject variability in everyday activity patterns. A patient’s level of mobility cannot be reliably estimated from the quality of movement. The quantity of movement in daily life should also be measured [2].

To acquire needed data during daily life, wearable devices provide very good solution. Complicated wearable systems such as garments with embedded sensors are designed as an undershirt with various sensors embedded within them. Data are transmitted to a pager-size device attached to the waist portion of the shirt where it is sent via a wireless gateway to the Internet and routed to a data server where the actual monitoring occurs. Optical fibers, a data bus, a microphone, other sensors, and a multifunction processor, all embedded in a basic textile grid [3].

Inertial measurement units (IMUs) are used as a subset of wearable devices to monitor the motion of human movement [4]. They are used to measure applied acceleration and angular velocity along and around a defined axis. The availability of commercial small and light-weighted wearable modules with an extended battery life allows for monitoring human movement for prolonged periods of time and without space limitations. IMUs can be used as a stand alone device or a combination of sensors placed on various parts of the body of the subject.

The presented study is a part of a PRIN’07 project (PI Prof. Della Croce). Its main goal is the evaluation of the mobility of healthy individuals living in an urban context in relation with fitness level, age and gender. Our research is focused on the biomedical engineering portion of the project. Main tasks are related to inertial sensor data enhancement for detection and classification of activities, and, analysis and interpretation of enhanced data.

4.2 Material and Methods

Data were acquired using a single IMU (FreeSense, Sensorize®) featuring a tri-axial accelerometer and two bi-axial gyroscopes (sampling frequency 50 Hz) placed at the waist level on the right body side level, with its x-axis pointing downwards, the y-axis pointing backward and the z-axis pointing to the left (Figure 4.1). Training data set was acquired on ten subjects (four females, 31±4 yrs) who performed the following dynamic activities: walking, walking up/down stairs, turning, sit-to-stand, and stand-to-sit. Static activities performed were: standing, sitting. The subjects were guided by an examiner, who identified the timing of each activity, throughout the 5 minutes long acquisitions. Ten acquisitions were made for each subject. First, the distinction between dynamic and static activities was accomplished. Then, two different approaches were used for each activity type. Static activities were distinguished based on the relative angle with respect to the gravitational acceleration direction. For the dynamic activities a neural classifier was used. Distinguishing static and dynamic activities allows the neural classifier to focus on fewer types of activities aimed at increasing its accuracy (Figure 4.2).

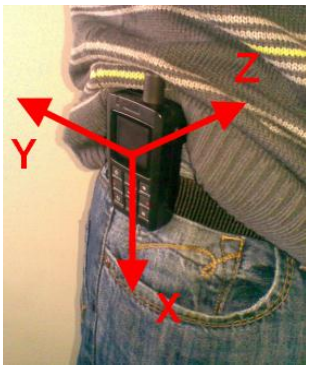

Figure 4.1 – Orientation of IMU

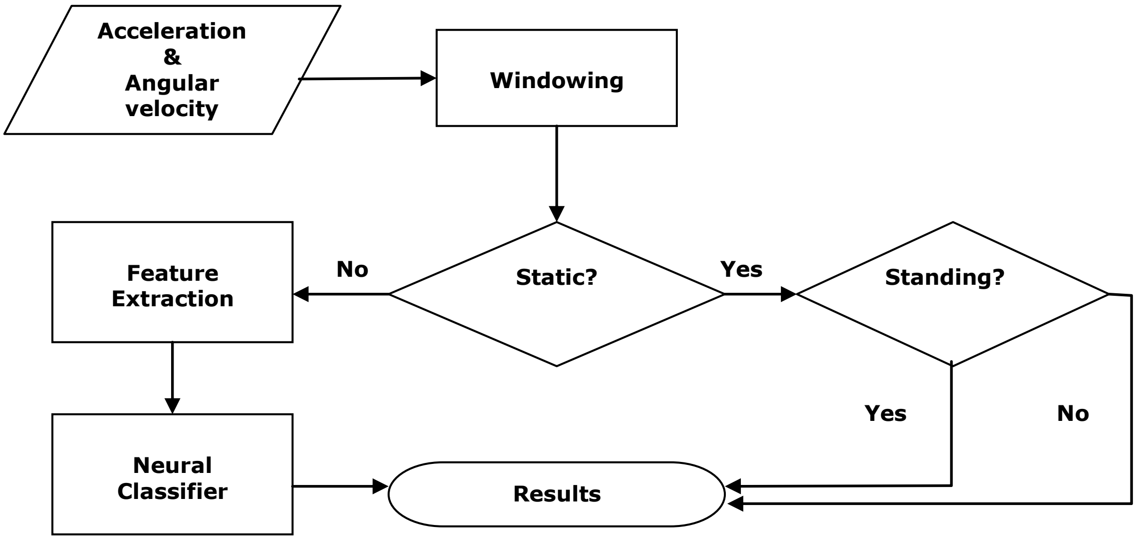

Figure 4.2 – The block diagram of activity recognition process

4.2.1 Distinguishing intervals of activity

Intervals of physical activity were the combinations of two different estimations; one estimated from acceleration signals ($a(t_i)$) and the other one from gyroscope signals ($w(t_i)$), by applying minimum activity thresholds to $a(t_i)$ and $w(t_i)$ included within a moving window (window size 1s, sliding step 0.1s) . When the two estimates, obtained from $a(t_i)$ and $w(t_i)$, did not match, the interval of activity was defined as the minimum time interval including them. The abovementioned procedure allowed dissecting the signals into subsequent parts.

Time intervals estimated from IMU is compared with a commercial physical activity assessment device. Estimated intervals are an array of true or false values (True meaning activity, false meaning no activity is occurring). Comparison is made by applying XOR operation to the intervals estimated and acquired from validation device.

4.2.2 Activity Classification

To classify the activities performed, machine learning methods are being used. Artificial neural networks are one of those methods. They are modeled after simple working logic of neural cells. ANN is an adaptive system that changes its structure based on information that flows through the network during the learning phase. ANNs are non-linear statistical data modeling tools, used to model complex relationships between inputs and outputs or to find patterns in data. In traditional statistical language, the inputs are the independent variables and the outputs are the dependent variables. They have a very wide range of applications including gait analysis [5]. To utilize ANNs, extracted features from accelerometer data should be fed into the network for training. After training, ANN will have the mapping from input data to classified activities (Figure 4.3).

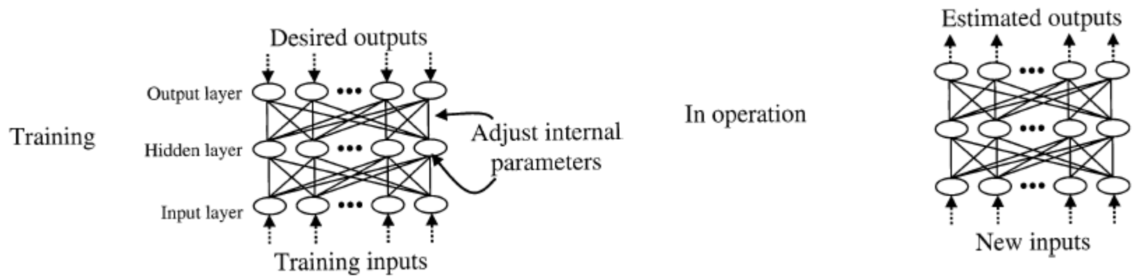

Figure 4.3 – Training procedure and operation of ANN

Multilayered feed-forward artificial neural network (ANN) [5] with the resilient backpropagation (RPROP) learning algorithm [6] was used to train the neural classifier. The ANN presented two hidden layers and a hyperbolic tangent sigmoid transfer function was used as transfer function for each layer (Figure 4.4). The signal inspection is performed using a sliding window approach, with window size 128 samples (2.56s) and 64 samples (1.28s) overlapping between each consecutive window.

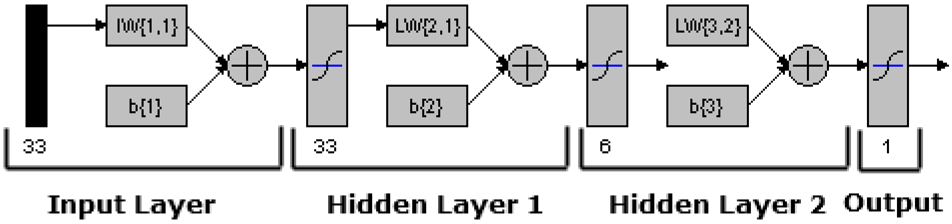

Figure 4.4 – General structure of ANN used

For each window, features characterizing the signal were extracted from the IMU signals. The selected features were:

(1) the mean value of the signal within the window interval,

(2) the standard deviation of the window interval,

(3) the energy content (sum of squared FFT component magnitudes divided by the window length),

(4) correlation between signals in the interval of window.

The correlation was useful for differentiating among activities in which most of the movement is along a sensing axis. For example, walking and running feature the largest displacement in one of the sensor directions, whereas stair climbing involves a displacement in a combination of two sensor directions. Effectiveness of these features was demonstrated in prior work [7, 8]. Thirty-three features for each window were extracted: six features (three for the acceleration and three for the angular velocities) for mean, standard deviation and energy and, fifteen features for correlation were calculated. 75% of data acquired were used for training, 15% for validation and 10% of the acquired data is used for testing the method.

4.3 Results

Average recognition rate for the whole process is 95.21%. Confusion matrix is in Table 4.1. In the matrix columns represents actual activities annotated at the preliminary acquisitions and rows represent results of the activity classification process. For example, column 1 implies that 86 of out of 87 inputs annotated as *standing* is classified correctly and 1 of the *standing* is confused with sitting. On the other hand looking at row 1, out of 95 activities classified as s*tanding*, 86 of them are actually *standing.* From the table it is seen that generally activities did not confused with each other. Although the system recognizes 94.19 % of the actual *stairs up,* it tends to confuse *walking* and *stairs down* activities with *stairs up*. Also for the *sit to stand* activity type the system has a low recognition rate.

		Actual Activity							
		Standing	Sitting	Walk	Stairs Up	Stairs Down	Sit2Stand	Stand2Sit	Turns
Classified Activity	Standing	86	9	0	0	0	0	0	0
	Sitting	1	59	0	0	0	0	0	0
	Walk	0	0	172	3	0	0	0	0
	Stairs Up	0	0	5	81	5	0	0	0
	Stairs Down	0	0	0	2	78	1	1	0
	Sit2Stand	0	0	0	0	0	22	0	1
	Stand2Sit	0	0	0	0	0	1	23	1
	Turns	0	0	0	0	0	0	0	76

Table 4.1 – Confusion matrix

Table 4.2 shows recognition rates and validity rates. Those values are compiled from the results shown in Table 4.1. Recognition rate column shows the percentage of actual activities classified correctly. Accuracy rate column shows the percentage of predicted activities classified correctly.

	Recognition rate	Accuracy rate
Standing	98.85	90.53
Sitting	86.76	98.33
Walk	97.18	98.29
Stairs Up	94.19	89.01
Stairs Down	93.98	95.12
Sit2Stand	91.67	95.65
Stand2Sit	95.83	92.00
Turns	97.44	100.00

Table 4.2 – Recognition and validity rates

4.4 Conclusion

The classification method has a high recognition rate in general (95.21%). But for some of the activity types (such as sit to stand) it can not perform well enough. One of the reasons for this is that transition activities has a smaller duration than periodical activities. Also the system has a low recognition rate for sitting posture. Since the orientation of the device regarding gravitational force was used for the detection of postures (classified as static intervals), it tends to confuse it with standing posture depending on the posture of the subject while seated. One solution for this problem is to apply some post processing for static intervals and classify intervals between transitions stand to sit and sit to stand, as sitting.

4.5 References

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CHAPTER 5

A SINGLE IMU FOR MOTION MEASUREMENTS

(This chapter was written on the basis of the accepted article "Bilateral step length estimation using a single inertial measurement unit attached to the pelvis"(Kose A., Cereatti A., Della Croce U. Journal of NeuroEngineering and Rehabilitation, 2012 (in press).)

5.1 Introduction

The measurement of temporal and spatial features of gait is essential for the assessment of gait abnormalities and the quantitative evaluation of treatment outcomes [1]. In particular, amplitude, variability and asymmetry of step length (SL) have been shown to be effective outcomes of walking ability. In fact, they are strongly related to the propulsion generation and can be representative of the compensatory mechanisms adopted in pathological walking [2, 3]. Having access to instruments capable of gathering information about the patient walking ability during daily life with no space limitations and for prolonged periods of time is of paramount importance in numerous clinical applications [4].

Inertial measurement units (IMU) are strong candidates for these applications. Those IMUs featuring 3-axis accelerometer and gyroscope [5] can be employed to estimate the SL during walking. In fact, an estimate of the SL can be obtained by first removing the contribution of the gravitational acceleration from the accelerometer signals, then by expressing the resulting acceleration in a global reference frame (GF) [6, 7], and finally, by double integrating its component in the direction of progression (DoP) between the instants of two consecutive heel strikes (HS).

However, the implementation of the procedure described above requires the solution of a number of critical issues:

a) the identification of the foot contact time instances (gait events),

b) the determination of the IMU orientation with respect to the GF [8],

c) the compensation for the drift affecting the accelerometer and gyroscope signals [9, 10],

d) the estimation of the initial velocity values for the integration of the acceleration along the DoP [11].

The most straightforward solution to determine both right and left SL (*r*SL and *l*SL) would be to place an IMU on each foot so that velocity and the orientation of each IMU can be set to zero at the beginning of the integration interval [6, 12, 13].

However, when the focus is on the description of the individual motor capacity ("can do in daily environment") and performance ("does do in daily environment") [14], the requirement of a light, small and minimally obstructive setup is of primary importance and, therefore, it would be desirable to obtain the same information using a single, discomfort-free IMU.

To the authors' knowledge, all the studies in the literature, based upon the use of a single IMU, determined the SL through indirect estimation methodologies [15, 16, 17].

Zijlstra and Hof (2003) proposed a method for estimating spatial-temporal parameters of gait from trunk accelerations. The IMU was placed on the back at the level of the S2 vertebrae. The method used zero crossing of the forward accelerations for detecting foot contact instances and an inverted pendulum model to estimate the SL. However, in their method, left and right foot contacts identification failed for 6 out of 15 subjects, 12% of the times and the SLs were underestimated in all subjects and at all speeds.

Gonzales and colleagues (2007) proposed a modified version of the pendulum model for taking into account the single stance and double-stance, separately. The IMU was placed on the back at the L3 vertebral level. Traversed distance estimation ranged between 94.5% to 106.7% of the actual traversed distance. No information was provided about the errors associated to the SL estimates.

Shin and Park (in press) determined the SL using a linear combination of the walking frequency and the variance of the signals of the accelerometer positioned in the back of a subject. Experiments were carried out on a single subject. The accuracy of the SL estimation is not reported, but the accuracy of traversed distance resulted to be of about 96%.

This study presents a method for the estimation of *rSL* and *lSL* during level walking using a single IMU attached to the pelvis. As every similar method, the proposed method requires the identification of the gait events as a preliminary step. To minimize the detrimental drift effects, the IMU acceleration along the DoP, obtained using a Kalman filter [18], is double integrated by means of a combination of direct and reverse integrations [19] of an optimally filtered acceleration along the DoP combined to a velocity update for the estimation of the initial values of its integral (the initial velocity).

We hypothesized that the proposed method for the estimation of the SL, would be more accurate than the indirect methods based on the use of inverted pendulum or regressive models.

The performance of the proposed approach was evaluated on data collected on healthy subjects walking at various speeds, using stereo-photogrammetric (SP) measurements as a gold standard.

5.2 Methods

5.2.1 Instrumentation

An IMU (FreeSense, Sensorize®) featuring a tri-axial accelerometer and two biaxial gyroscopes (acceleration resolution 0.0096 m/s2, angular rate resolution 0.2441 deg/s, unit weight 93 g, unit size 85 mm × 49 mm × 21 mm) sampling data at 100 frames/s was used. A 10-camera BTS® SMART-D stereo-photogrammetric system acquiring at 100 frames/s, was used for validation purposes.

5.2.2 Step length estimation

The method described below can be applied to the data obtained from any IMU featuring a tri-axial accelerometer and a three axial gyroscope. The physical quantities, specific forces and angular velocities, provided by each sensors of the IMU, are measured with respect to the axes of a local frame (LF) aligned to the edges of the unit housing. In this application, the IMU was mounted on the right side of the body at the pelvis level with X_L, Y_L and Z_L axes pointing downward, forward, and to the right, respectively (Figure 5.1).

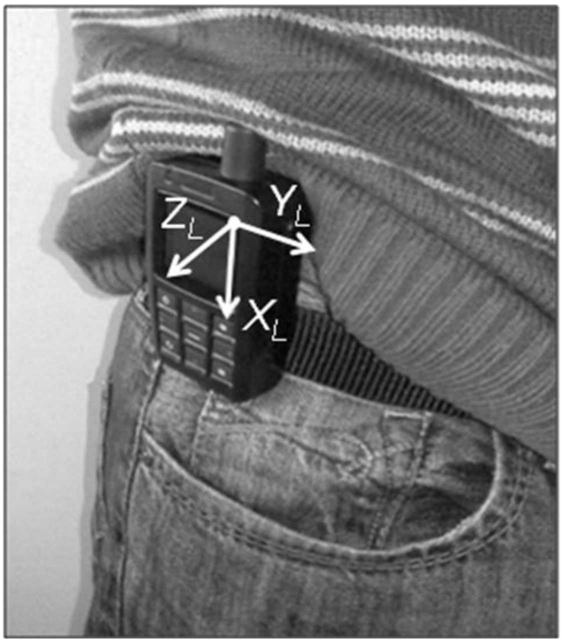

Figure 5.1. The IMU location – The IMU attached to the belt and positioned to the right side of the subject pelvis and relevant LF.

The assumption that the pelvis displacement along the DoP between the beginning and the end of a gait cycle occurs in phase with the movement of the feet is the basis of the proposed method. The success of the method relies on the solving of following issues:

a) the identification of gait events;

b) the determination of pelvis displacement along the DoP.

A common approach to deal with the former was used in this study and an original method was developed to solve the latter.

5.2.3 Identification of gait events

A gait cycle begins when a foot hits the ground (heel strike - HS) and ends when the next HS of the same foot occurs. When gait cycles can be identified for both sides, then also steps can be identified. A step begins when a contra-lateral HS occurs and ends at the first following HS.

In this study, initial and final contact of each recorded gait cycle for both sides were identified from the IMU signals. By following a heuristic approach, a preliminary visual investigation was performed to correlate the distinctive features in the IMU signals with the relevant gait events extracted from the SP system data (Figure 5.2a).

A wavelet-based method was used to identify the candidate time instances from the accelerometer signals. The XL and YL accelerometer signals were decomposed using“Stationary wavelet decomposition” [20]. A Daubechies level 5 (“db5”) mother wavelet was chosen given its similarity to the IMU signals in the proximity of HS. The original signals were then decomposed in an approximation curve plus ten levels of detail. Thresholds were applied to the first three detail levels and the other detail levels were discarded. Thresholds for these levels were 1/5, 1/4 and 1/3 of its magnitude for the first, second and third level, respectively. The signals were reconstructed using only the first three levels of detail after thresholds were applied. An interval of interest for the accelerometer signals was defined as the interval of time during which the reconstructed signals differed from zero (Figure 5.2b and Figure 5.2c).

The right HS (rHS) was detected as the instant of time in the middle between the maximum of the YL accelerometer signal and the first minimum of the accelerometer signal along the XL accelerometer signal in the corresponding intervals of interest. The identification of the left HS (lHS) required the identification of both right and left toe off instances (rTO, lTO). The lTO was detected as the instant of time in the middle between the first maximum of the YL accelerometer signal after the rHS and the second minimum of the XL accelerometer signal in the corresponding intervals of interest. The rTO was found as the time of the minimum negative peak value between two consecutive lTO and rHS. The lHS was found as the first local maximum of the ZL accelerometer signal before the rTO (Figure 5.2d) [21].

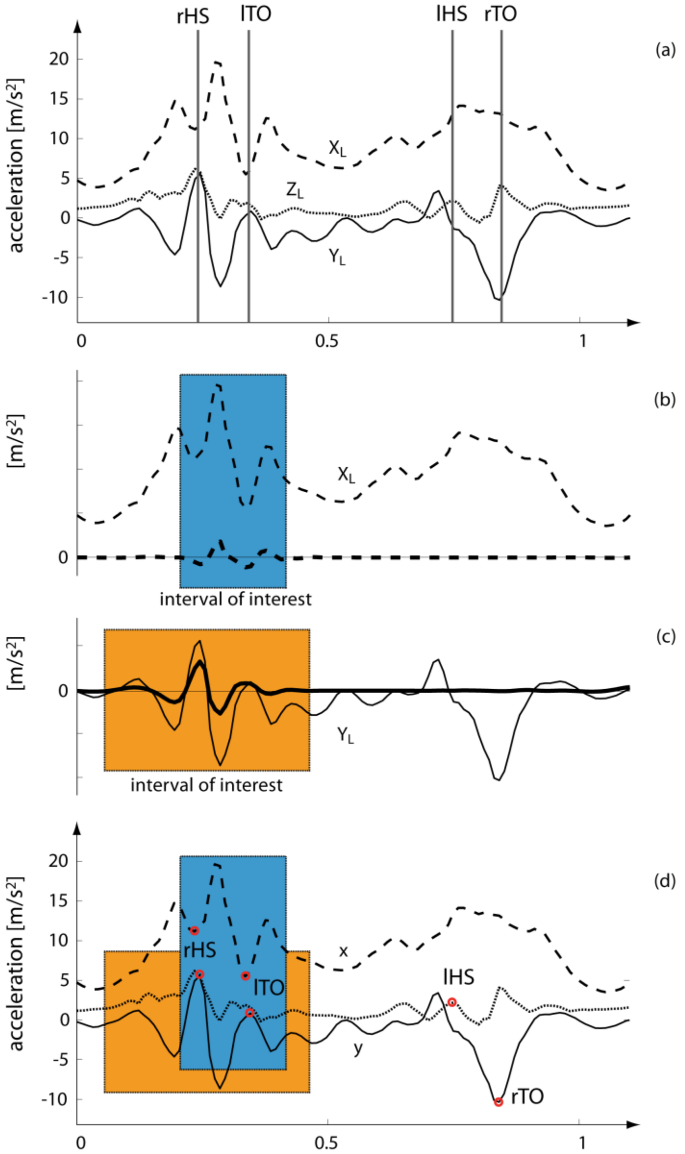

Figure 5.2. IMU signals and relevant gait events (a) Raw accelerometric signals: XL pointing downward (dashed line), YL pointing forward (solid line) and ZL pointing laterally (dot-dashed line). SP-based gait event timings are superimposed (vertical lines). (b) Raw signal on XL and corresponding reconstructed signal (thick dashed line) used for the definition of the interval of interest. (c) Raw signal on YL and corresponding reconstructed signal (thick line) used for the definition of the interval of interest. (d) Circles show the reference points used to estimate gait events from the accelerometric raw signals.

5.2.4 Estimation of the pelvis displacement along the DoP

The method developed for estimating the pelvis displacement along the DoP requires the knowledge of the gait events and is divided in the following phases:

a) estimation of the IMU acceleration along the DoP;

b) integration of the IMU acceleration along the DoP;

and, when the IMU is located laterally,

c) removal of pelvic rotation contribution to IMU displacement.

5.2.5 Estimation of the IMU acceleration along the DoP

To estimate the IMU coordinate acceleration along the DoP, the orientation of the LF_{IMU} with respect to the global frame (GF_{IMU}), was estimated using a specifically designed Kalman Filter [Mazzà et al., in press].

The GF_{IMU} was defined as follows: the X_G axis coinciding with the direction of gravity, the Y_G axis coinciding with the DoP of the subject during level straight walking, t, and the Z_G resulting from the cross product between X_G and Y_G .

The orientation of LF_{IMU} with respect to GF_{IMU} at the i^th instant of time was expressed using the orientation quaternion ${}^{G}\mathbf{q}_{L}(i)$.

Let ${}^{L}\mathbf{f}(i)$ be the specific force vector measured by the IMU expressed in LF_{IMU} at the i^{th} instant of time, then the coordinate acceleration vector ${}^{G}\mathbf{a}(i)$ expressed in the GF_{IMU} can be computed as:

$$ {}^{G}\mathbf{a}(i) = {}^{G}\begin{bmatrix} a_x(i) \\ a_y(i) \\ a_z(i) \end{bmatrix} = \begin{bmatrix} 0 \\ -g \\ 0 \end{bmatrix} + {}^{G}\mathbf{q}_{L}(i)\, {}^{L}\mathbf{f}(i) \tag{1} $$

5.2.6 Integration of the IMU acceleration along the DoP

To obtain the velocity and displacement time series along the DoP, an integration technique, the Optimally Filtered Direct and Reverse Integration (OFDRI), and its simplified version, the Optimally Filtered Integration (OFI) [19], was adapted to manage acceleration signals during gait. Both the OFI and the OFDRI were originally designed for step negotiation motor tasks [19] and require the knowledge of the final value of the integral to set a cut off frequency for the high pass filter employed to reduce the effect of the drift in the accelerometer signals. In this application, the cut off frequency was determined from a gait cycle for which the initial and final velocity of the IMU was assumed to be equal. The resulting cut-off frequency was then applied for filtering the acceleration signal along the DoP, one gait cycle at a time. Since the trials started with the subject standing, the initial velocity along the DoP was set to zero. The velocity values found for the final HS were used as initial velocity values for the integration of the following gait cycle. For those gait cycles where the velocity at the final HS resulted to be roughly equal to the initial value ($\pm \varepsilon$, $\varepsilon = 0.3$ m/s), then it was forced to be exactly equal to it and the OFDRI was applied. The same updated velocity value was used also as initial velocity of the following gait cycle. The value $\varepsilon = 0.3$ m/s was chosen based on a trial and error approach.

The second integration, the integration of velocity along the DoP to obtain displacement, was performed following the same approach. Since, for all cycles, the final value of the integral (the displacement at the final HS) could be neither known nor estimated, OFDRI was never applied and final values of the integral were never updated.

Therefore, the resulting estimates of *rSL* and *lSL* of the j^{th} gait cycle were:

$rSL_j=[s_x(rHS_j)- s_x(lHS_j)] - d\sin(\theta_j)$

$lSL_j=[s_x(lHS_j)- s_x(rHS_j)] + d\sin(\theta_j)$

where s_x is the displacement along the DoP.

The SL estimation method including the estimation and integration of the IMU acceleration along the DoP was named KOSE (Kalman and Optimal based filtering Step length Estimation).

5.2.7 Removal of pelvic rotation contribution to the IMU displacement

During walking, the pelvic rotation contributes to the length of steps since it completes a full cycle every two steps. When the IMU is located on the right side of the pelvis, the IMU displacement along the DoP, at the end of the right step duration (*rT*, the time interval between a *lHS* and the following *rHS*), is larger than the actual *rSL* due to the pelvic angular displacement θ occurring during the same interval of time. Conversely, the IMU displacement at the end of the left step duration (*lT*, the time interval between the *rHS* and the *lHS*) is smaller than the *lSL*. Therefore, applying the equations (2) without taking into account the pelvic rotation, would result in an overestimate of the *rSL* and an underestimate of the *lSL* (vice versa if the IMU is attached to the left side of the pelvis). The amount of the over-(under-) estimate would be equal to $d\sin(\theta_j)$, where d is the inter ASIS (anterior superior iliac spine) distance, and θ_j is the pelvic angular displacement between beginning and end of the j^{th} cycle.

Therefore, for the j^{th} gait cycle, *rSL* and *lSL* can be obtained as:

$rSL_j=[s_x(rhs_j)- s_x(lhs_j)] - d\sin(\theta_j)$

$lSL_j=[s_x(lhs_j)- s_x(rhs_j)] + d\sin(\theta_j)$

when the IMU is on the right side of the pelvis and as:

$rSL_j=[s_x(rhs_j)- s_x(lhs_j)] + d\sin(\theta_j)$

$lSL_j=[s_x(lhs_j)- s_x(rhs_j)] - d\sin(\theta_j)$

when the IMU is on the left side of the pelvis.

5.2.8 Experimental Session

Gait data of nine healthy subjects (31 ± 6 yrs) were acquired. Two markers were placed on the right and left heels and toes of each subject. Subjects were asked to walk along a closed loop track of 25 m varying their speed as follows. They started walking from a standing position with their heels aligned to the start line. For the first two laps they walked at slow speed. At the beginning of the third lap, they increased their speed (comfortable speed) and maintained it for the third and fourth laps. At the beginning of the fifth lap, they further increased their speed (fast speed) and maintained it for the fifth and sixth laps. At the beginning of the seventh lap, they decreased their speed (comfortable speed) and maintained it for the seventh and eighth laps. At the beginning of the ninth lap, they further decreased their speed (slow speed) and maintained it for the ninth and tenth laps. They stopped walking at the end of the tenth lap (Figure 5.3b).

A 4 m long portion of the walking track was included in the calibrated volume of the SP system, (Figure 5.3a) with its reference frame made to coincide with the GF. For each lap, SP data of three consecutive gait cycles were recorded.

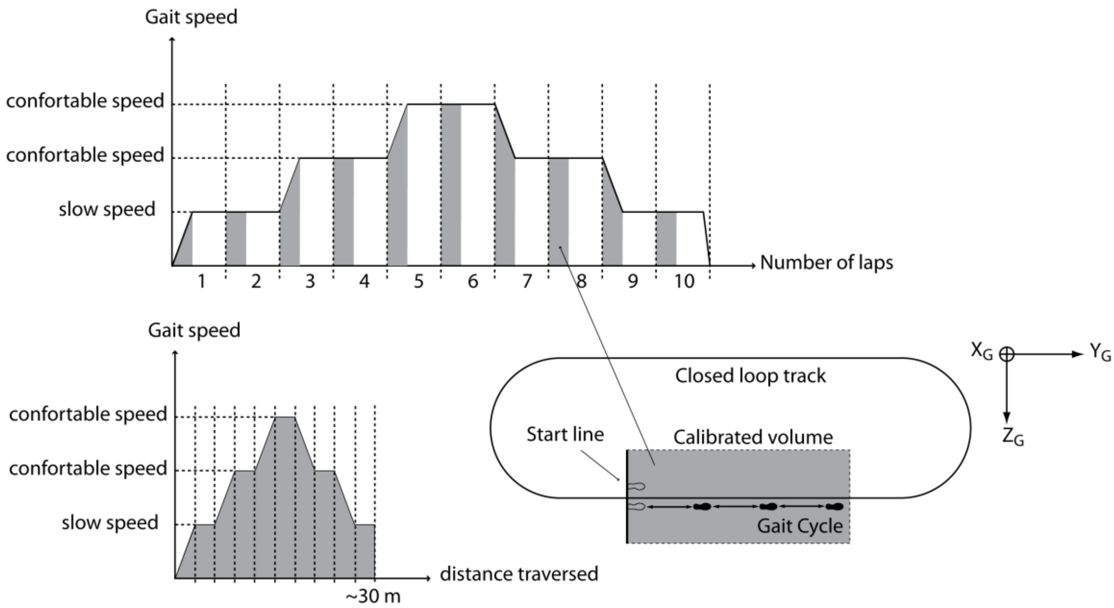

Figure 5.3. Experimental data acquisition – A schematic view of the path and the calibrated volume (seen from above).

Only data recorded by the IMU and SP system within the calibrated volume were used for the method validation. Data recorded during each lap were arranged together to obtain a continuous data set formed by 3 × 10 gait cycles (Figure 5.3c).

5.2.9 Data analysis

The estimates of the timing of the gait events (rHS, lHS), the right and left step duration (rT, lT) and of *rSL* and *lSL*, obtained from the heel marker coordinates reconstructed with the SP system were used as gold standard measurements when evaluating the accuracy of the estimates obtained using the IMU.

Thus, for each step *j* and for any given quantity, the differences between IMU estimates and gold standard measurements may be interpreted as estimation error:

$$e_{rHS_j} = rHS_{IMU,j} - rHS_{SP,j}$$
$$e_{lHS_j} = lHS_{IMU,j} - lHS_{SP,j}$$
$$e_{rT_j} = rT_{IMU,j} - rT_{SP,j}$$
$$e_{lT_j} = lT_{IMU,j} - lT_{SP,j}$$
$$\%e_{rT_j} = \frac{rT_{IMU,j} - rT_{SP,j}}{rT_{SP,j}}$$
$$\%e_{lT_j} = \frac{lT_{IMU,j} - lT_{SP,j}}{lT_{SP,j}}$$
$$e_{rSL_j} = rSL_{IMU,j} - rSL_{SP,j}$$
$$\%e_{rSL_j} = \frac{rSL_{IMU,j} - rSL_{SP,j}}{rSL_{SP,j}}$$
$$e_{lSL_j} = lSL_{IMU,j} - lSL_{SP,j}$$
$$\%e_{lSL_j} = \frac{lSL_{IMU,j} - lSL_{SP,j}}{lSL_{SP,j}}$$

Descriptive statistics of the above errors were computed.

In addition, to compare our results with previous works, the difference between the IMU estimated distance and the actual traversed distance was computed for each subject.

5.3 Results

Cut-off frequencies employed in both OFI and OFDRI to high-pass filter the original data varied, across the subjects, between the 0.067 Hz and 0.096 Hz. The pelvic rotation was on average across subjects about 5 degrees.

5.3.1 Heel strike detection

All *rHS* and *lHS* instances were successfully detected in all subjects. The mean and standard deviation of errors e_{rHSj} and e_{lHSj} are reported in Table 5.1. On average, the IMU-based estimates of both *rHS* and *lHS* were delayed with respect to the corresponding SP estimates by 0.017 s and 0.027 s, respectively.

[s]	RHS		LHS	
subject	mean	s.d.	mean	s.d.
1	0,019	0,027	0,026	0,019
2	0,008	0,021	0,017	0,016
3	0,026	0,017	0,034	0,021
4	0,012	0,007	0,027	0,025
5	0,021	0,031	0,029	0,019
6	0,016	0,013	0,028	0,024
7	0,024	0,022	0,031	0,017
8	0,018	0,02	0,028	0,016
9	0,009	0,019	0,019	0,025
average	0,017	0,020	0,027	0,020

Table 5.1 – **Heel strike detection error** - Mean and standard deviation of errors in detecting right and left heel strikes are reported for each subject. Averaged values across the nine subjects are also reported. All values are in seconds.

5.3.2 Right and left step duration

The mean and standard deviation of errors *erTj* and *elTj* together with the mean percent errors are reported in Table 5.2. On average, across subjects, the IMU-based estimates of *rT* were 0.015 s (-2.3%) shorter than the SP measurements. On the contrary, the IMU-based estimates of *lT* were 0.017 s (+2.4%) longer than the SP measurements. On the contrary, the IMU-based estimates of *lT* were 0.017 s (+2.4%) longer than the SP measurements.

[s]	rT			lT		
Subject	mean	s.d.	%	mean	s.d.	%
1	-0,021	0,031	-3,10%	0,024	0,025	2,60%
2	-0,015	0,026	-2,80%	0,011	0,017	2,60%
3	-0,014	0,017	-2,10%	0,023	0,019	2,70%
4	-0,009	0,013	-1,70%	0,017	0,017	2,90%
5	-0,014	0,022	-1,90%	0,011	0,023	1,60%
6	-0,011	0,021	-1,50%	0,016	0,019	2,00%
7	-0,022	0,027	-3,20%	0,019	0,025	2,70%
8	-0,017	0,021	-2,50%	0,024	0,025	3,20%
9	-0,01	0,018	-1,50%	0,009	0,018	1,40%
Average	-0,015	0,022	-2,26%	0,017	0,021	2,41%

Table 5.2 - Step lenghts - Mean differences and standard deviations between step length values estimated with the IMU and with stereophotogrammetric system. All values are in meters.

5.3.3 Right and left SL estimation

The mean and standard deviation of errors e_{rSLj} and e_{lSLj} together with the mean percent errors are reported in Table 5.3. Percent errors varied across subjects, between -2.6% and +2.9% for the *rSL* and between 0.4% and 2.6% for the *lSL*. On average, across subjects, IMU-based estimates of *rSL* were slightly overestimated by 0.009 m (+1.2%).

On the contrary, *lSL* were underestimated by 0.008 m (-1.1%).

[m]	erSL			elSL		
subject	mean	s.d.	%	mean	s.d.	%
1	0,014	0,016	2,0%	-0,010	0,014	-1,9%
2	0,020	0,015	2,9%	-0,017	0,013	-2,6%
3	0,006	0,015	0,8%	0,002	0,016	0,3%
4	-0,001	0,021	-0,2%	0,002	0,019	0,4%
5	0,017	0,018	2,1%	-0,012	0,018	-1,5%
6	0,019	0,019	2,1%	-0,019	0,021	-2,2%
7	0,013	0,015	1,7%	-0,008	0,014	-1,1%
8	-0,008	0,017	-1,2%	0,001	0,019	0,2%
9	0,003	0,013	0,6%	-0,012	0,013	-1,4%
average	0,009	0,017	1,2%	-0,008	0,016	-1,1%

Table 5.3 - Total traversed distance - Mean differences and standard deviations between step length values estimated with the IMU and with stereophotogrammetric system. All values are in meters.

5.3.4 Total traversed distance

The actual and IMU-based estimates of the traversed distance are reported in Table 5.4. Percent errors over a traversed distance of about 30 m, varied across subjects, between -0.54 m (-1.6%) and 0.54 m (+1.7 %). The average estimate of the traversed distance is equal to 0.1%.

subject	actual distance [m]	estimated distance [m]	difference [m]	%difference
1	32,65	33,02	0,37	1,1%
2	30,99	31,46	0,46	1,5%
3	31,17	30,80	-0,37	-1,2%
4	31,71	32,25	0,54	1,7%
5	30,37	29,91	-0,46	-1,5%
6	33,44	32,89	-0,54	-1,6%
7	31,40	31,74	0,34	1,1%
8	32,11	31,78	-0,33	-1,0%
9	30,63	31,00	0,37	1,2%
average	31,61	31,65	0,04	0,1%

Table 5.4 - Total traversed distance - Actual and estimated traversed distance (in meters) obtained from the SP and IMU data respectively, along with the difference (in meters) and percentage difference. Averaged values across the nine subjects are also reported.

5.4 Discussion and Conclusion

A method for determining both right and left SL during level walking using a single IMU to be used either indoor or outdoor, without space limitations and for prolonged periods of time, was presented and validated.

SL estimates were obtained directly from the IMU displacement between two consecutive HS, by employing an original method (the KOSE method) which double integrates the IMU acceleration along the DoP obtained after applying a Kalman filter. To reduce the errors caused by the drift affecting the IMU acceleration along the DoP, an integration technique proposed by Zok and colleagues [19] was adapted to gait and used.

The method was tested on healthy subjects while they were walking increasing and decreasing their speed, five times along 30 m. The algorithm for the identification of left and right HS never failed in all the subjects analyzed. Both right and left HS were detected with an average time delay corresponding to 1.7 samples and 2.7 samples, respectively (sample frequency 100 frames/s). These errors implied that the right step duration was on average two samples shorter than the left one. Despite the shorter estimated step duration, the *rSL* resulted, over the different subjects, overestimated by 1.2%. The maximum mean error in estimating the SL was overestimated by 2.9% for the *rSL* and underestimated by 2.6% for the *lSL*. The main explanation for the side to side differences, is probably that the effect of the pelvic rotation, associated to the asymmetrical IMU positioning, was not completely compensated for by the correction term $d\sin(\theta_j)$. In fact, in this regard, several assumptions were not completely satisfied: being attached to the belt of the subject, the IMU was not rigidly moving with the pelvis and d, which is taken as the inter-ASIS distance may differ from the distance between the LF origin to the pelvis vertical axis of rotation. As expected, the maximum percent error on the total traversed distance was to 1.7% and therefore smaller than the maximum SL percent error. It is worth noticing that the estimate of the traversed distance was never consistently either an overestimate or an underestimate (average over subjects equal to 0.1%).

Several methods to estimate *rSL* and *lSL*, using a single IMU, have been proposed in the literature [15, 16, 17, 22]. A common feature of these methods is that the SL estimates were derived using indirect methodologies, either based on inverted pendulum models for level human walking representation [23, 24] or based on general regressive equation in which SL is expressed as function of the step frequency and accelerometric signal variations. Unfortunately, no data on the accuracy of the *rSL* and *lSL* estimates were provided in abovementioned studies. Therefore, a straightforward comparison among methods is not possible. However, Zijlstra and Hof (2003) reported a consistent

SL underestimation. As a consequence, also the mean speed (mean SL divided mean step time) was underestimated and to correct it, they introduced a coefficient of 1.25 heuristically determined. It could then be inferred that the SL estimations were affected by errors of about 20-30%. In Gonzales and colleagues (2007), the performance of their method was evaluated by assessing the errors of the distance traversed in each acquisition. Across subjects, errors ranged from -6.5% to +6.0%. Shin and Park (in press) reported an accuracy error of 3.7% (worst case) for the traversed distance. In our study the errors in estimating the traversed distance ranged from -1.6% to +1.7% among subjects.

The smaller estimation errors compared to previously publish methods, confirm our initial hypothesis that the KOSE method improves the accuracy with respect to indirect methods based on the use of general models, which may not always take into account subject specificity in gait.

In this study, the IMU was attached to the subject's belt on the right side. This location was chosen to reduce subject discomfort and because it is a practical solution for monitoring daily life motor activities. However, it can be hypothesized that attaching the IMU centrally in the back (S2 or L3 vertebral level) similarly to Zijlstra and Hof (2003) Gonzales and colleagues (2007) and Shin and Park (in press), the residual errors related to the pelvic rotation correction would be reduced and it would not be necessary to correct for the pelvic rotation effects.

In this study we presented results relative to gait event timings and SL estimations. Additional gait parameters can be easily calculated from the estimated parameters. Therefore, using a single IMU, we were able to provide excellent estimates of both temporal and spatial gait parameters bilaterally.

It is important to stress that the KOSE method was tested on experimental conditions fairly similar to those which can be encountered in the real life: different gait speeds (three gait speed levels), numerous velocity transients (five velocity transients on 30 m). It is reasonable to expect that, in healthy subjects, errors in traversed distance estimation during daily monitoring activity would be of the same order of magnitude of those presented.

The data set, derived from the experiments carried out in the present study, referred to a straight level walking. For this specific method validation, the GF was therefore defined, at the beginning of each acquisition with the Y_G axis coinciding with the DoP. The IMU acceleration component along the DoP, was then calculated by projecting the accelerometric signal, after having removed the gravitational contribution, on the GF. In general, if during the acquisition, the subject varies the DoP more than once, it is necessary to define for every different DoP, an auxiliary GF with the Y_G axis aligned to the relevant DoP.

There are some limitations to the current proof of concept which need to be addressed before using the presented methodology to estimate gait spatial and temporal parameters in clinical contexts. One issue is related to the algorithm used to identify the gait events, which is normally based on IMU signal features. Such features may change or even disappear in pathologic subjects. Another issue is related to the assumption that the pelvis displacement along the DoP between HS equals the SL. In fact, in some gait disorders the pelvis displacement may not be in phase with the feet displacement as much as in healthy subjects. Finally, a potential limitation of the KOSE method is that it performs better on gait with fewer fluctuations in speed since the OFDRI, which is very effective in reducing the IMU signal drift [25], can be used only when subjects walk at a constant speed.

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CHAPTER 6

APPLICATIONS OF METHODS

6.1 Motivation

The World Health Organization (WHO) includes physical inactivity among the first ten causes of mortality and functional capacity limitations in the world. On the other hand, physical inactivity is a factor, which, in theory, could be controlled or modified, as well as smoking and eating habits. Acknowledging the importance of physical activity made necessary the identification of reliable methods for its quantitative evaluation, which, instead, is usually made using questionnaires, typically qualitative and with little accuracy. It is known as the cardio-respiratory fitness, neuromuscular function and motor capacity tend to degrade with ageing. However, both the relationship among these three determinants of mobility and the association between their deterioration level and the amount of physical activity performed during the daily life are still unknown. The quantitative evaluation and the characterization of the cause-effect relationship between physical activity and mobility require the combined evaluation of the three determinants to be included. The evaluation of the physical activity performed by individuals during their daily life usually is based on the analysis of those activities which require a higher level of energy expenditure, such as the locomotion tasks (sit-to-stand, walking, running, stair climbing, cycling, etc.). The finer movements of upper limbs, fingers and neck are usually not included. Therefore, the level of physical activity may properly assessed by quantifying the daily performance of a selected group of motor tasks (assessment of motor performance).

6.2 Application on healthy subjects

The goal of the presented study was the identification and the application of novel and accurate methodologies for the evaluation of the mobility of healthy individuals living in an urban context, in relationship with their fitness level, age and gender. In order to reach such goal, both biomedical engineers and physical exercise physiologists will face important challenges. The most interesting engineering aspect is the assessment of the motor performance (methods for assessing motor capacity are better developed). Properly integrated wearable devices coupled with biomechanical models may provide the necessary information for the evaluation of the motor performance. Exercise physiologists will investigate the relationships among: a) cardio-respiratory fitness, b) neuromuscular function, c) motor capacity and d) physical activity levels, on samples of the age ranges (young adults, adults and elder adults) living in an urban context. Both biomechanical and physiological quantities obtained both from the laboratory and the daily life will be considered. The information extracted from the large pool of data formed will be performed using data mining techniques. The expected output of the entire process will be formed by a set of significant patterns and relationships among data, which will represent the knowledge extracted from the database. Such patterns will be used to characterize each group (differences in gender, age or fitness level) and will be expressed using relationships among the variables obtained from laboratory tests, from monitoring activities or both. It is expected that the information obtained will contribute in shaping a picture of the mobility level of the selected population.

With the presented motivation and the goal a PRIN'07 project was initiated with Prof. Ugo DELLA CROCE as its PI. The Research Unit (RU), that the author of the presented thesis was a member of, was in charge of the biomedical engineering part of the project. Specifically, two main activities were decided to be carried out by the research unit: (a) wearable sensor data enhancement through application of mechanical models and (b) the analysis and interpretation of wearable devices data combined to the physical activity laboratory data. The former activity included a validation of wearable device data. Test subjects were asked to perform movements frequently performed during daily life (sit-to-stand, walking, etc.) while wearing sensors in a motion analysis laboratory (featuring force platforms and motion capture system). The study presented on chapter 4 was developed to be used in this section of the application. The latter activity required the processing of selected biomechanical variables extracted from the wearable devices data and the biomechanical modeling complemented with motor and cardio-respiratory capacity, and neuromuscular function data. The study presented in chapter 5 aimed at meeting the requirements of this section of the application. Biomechanical modeling complemented with motor and cardio-respiratory capacity, and neuromuscular function data, was carried out by another research unit of the PRIN project.

6.2.1 Materials and methods

34 subjects participated in the study. 18 of the subjects were young (age = 28 ± 3 yrs) and 16 of them were elderly (age = 71 ± 4 yrs). Acquisitions were carried out for 24 hrs. A single IMU (FreeSense, Sensorize®) was attached with a protection cover to the belts of the subjects at the right side of the body. During the night, the subjects take out the device from their belts and put it back on in the morning, therefore for every acquisition approximately 16 hrs of activity data were acquired). A commercial validation device was used (IDEEA, Minisun®) for validation purposes. The commercial device had multiple sensors placed in various parts of the subject. The setup

presented in this thesis was used together with the commercial device without any interaction. An Artificial Neural Network (ANN) based algorithm that was presented in chapter 4 was used for the classification of activities. And for extracting the parameters of gait, the study presented in chapter 5 was used.

6.2.2 Results

The commercial device reports total durations of activities for given period (24 hrs). Table 6.1 shows the durations of activities, for each subject, estimated by the commercial device. The activities occurred during the night were not included in this table. The intervals for “night-times” to be excludeded were estimated from the FreeSense IMU output. (The subjects took out the IMU during sleep).

[min]	Commercial Device Activity Durations						
Subject	SITTING	STAND	WALK	STEPUP	STEPDOWN	StSi	SiSt
OF02	650,45	263,30	40,76	0,27	0,35	2,50	2,36
OF03	261,43	550,91	140,97	1,02	1,95	1,95	1,77
OF05	494,92	318,59	93,67	1,45	1,41	2,90	2,71
OF06	389,23	394,44	127,89	0,10	1,20	2,23	2,23
OF11	562,88	310,31	80,13	0,38	0,41	3,02	2,87
OM01	608,66	194,65	90,07	0,16	3,49	0,80	0,80
OM02	656,38	193,38	84,22	0,80	1,75	1,15	0,97
OM03	373,67	463,88	113,79	2,41	1,87	1,88	1,83
OM04	593,33	301,76	55,94	0,38	0,87	3,82	3,90
OM05	570,40	298,01	79,09	1,19	1,21	1,16	1,10
OM06	592,60	266,91	46,56	0,84	1,11	2,14	4,82
OM07	607,32	153,16	191,64	2,56	3,80	0,72	0,73
OM08	726,65	166,58	60,05	0,84	0,17	2,94	2,78
OM09	692,07	209,18	51,41	0,39	0,99	2,98	2,98
OM10	615,59	258,32	79,46	3,01	1,12	1,24	1,27
OM11	525,56	350,61	76,51	0,33	2,46	2,11	2,08
YF02	610,93	236,96	83,15	4,26	2,67	3,98	4,06
YF03	708,36	192,15	34,54	0,75	1,38	1,28	1,18
YF05	644,60	245,94	60,53	1,49	3,10	1,67	1,66
YF06	419,12	395,39	109,98	1,95	3,22	1,80	1,94
YF07	282,24	496,69	170,39	2,33	2,66	2,40	2,65
YF08	665,47	215,84	49,02	2,48	1,95	1,37	1,50
YF10	644,18	251,06	57,66	2,96	2,28	0,90	0,95
YF11	600,90	287,61	52,01	2,16	2,38	2,84	3,03
YF12	538,25	339,14	64,00	2,84	3,37	3,18	3,38
YM04	571,49	238,57	69,89	3,71	1,36	3,65	3,60
YM05	496,94	288,32	126,53	4,23	2,76	3,23	3,32
YM06	835,39	95,75	25,76	0,34	1,33	0,80	0,63
YM07	189,48	290,94	83,11	1,80	0,81	0,53	0,48
YM08	531,78	286,43	134,03	2,45	1,77	1,79	1,74
YM09	671,62	195,73	83,49	2,50	2,53	1,87	2,08
YM10	578,48	291,10	77,21	3,03	1,99	3,54	3,64
YM11	518,79	346,85	71,80	5,80	3,60	6,40	6,41
YM12	577,66	302,66	71,62	2,34	2,60	1,48	1,56

Table 6.1 - Durations of activities estimated by the commercial device. The values are given in minutes

Table 6.2 shows the durations of activities, for each subject, estimated by the proposed activity classification method that uses a single IMU.

[min]	Single IMU Activity Durations						
Subject	SITTING	STAND	WALK	STEPUP	STEPDOWN	StSi	SiSt
OF02	647,53	256,04	45,60	0,68	0,45	2,69	2,64
OF03	260,66	553,96	141,79	1,40	1,30	2,03	2,19
OF05	493,08	314,75	96,36	1,55	1,47	3,20	2,88
OF06	392,03	392,32	126,28	0,62	1,12	2,44	2,64
OF11	560,83	311,36	82,18	0,49	0,50	3,26	3,18
OM01	609,75	192,06	89,03	1,75	3,28	1,09	0,96
OM02	654,31	192,39	85,91	1,16	1,41	1,45	1,21
OM03	374,95	465,93	113,59	1,98	1,84	1,80	2,05
OM04	591,59	299,22	57,20	0,56	0,95	3,71	4,03
OM05	569,06	299,64	80,61	1,26	1,37	1,38	1,40
OM06	591,27	265,15	47,83	0,81	1,31	1,96	4,61
OM07	606,26	152,94	192,78	2,71	3,22	0,87	0,84
OM08	725,38	164,45	61,79	0,72	0,81	3,29	2,28
OM09	690,56	208,74	53,02	0,83	0,71	3,12	3,95
OM10	613,59	257,85	80,72	2,78	1,46	0,92	1,09
OM11	526,41	349,89	77,31	1,01	1,96	2,26	1,96
YF02	609,06	236,48	82,13	4,46	2,86	4,14	4,16
YF03	706,34	190,67	35,08	0,57	1,26	0,97	1,35
YF05	645,59	244,02	61,20	1,13	2,88	1,79	1,57
YF06	420,45	394,48	111,25	2,12	3,46	1,78	2,06
YF07	281,57	496,53	171,93	1,00	2,93	2,21	2,43
YF08	663,14	214,40	50,83	1,86	1,72	1,75	1,73
YF10	643,55	251,63	57,31	3,01	2,63	1,16	1,15
YF11	600,29	286,42	52,32	2,58	2,86	2,74	2,85
YF12	537,72	339,65	65,01	2,37	3,88	2,97	3,52
YM04	571,30	238,17	68,46	4,08	1,24	3,35	3,54
YM05	497,23	289,66	127,23	3,81	2,39	3,00	3,16
YM06	833,98	94,48	26,24	0,68	1,20	1,04	0,88
YM07	188,45	291,18	84,97	2,37	0,96	0,69	0,77
YM08	530,65	285,43	136,48	2,71	2,18	2,07	1,84
YM09	670,34	196,17	85,30	2,15	2,99	1,69	1,86
YM10	577,54	290,69	77,56	3,35	1,86	3,86	3,84
YM11	517,18	346,99	73,11	5,20	3,76	5,99	6,29
YM12	576,22	303,54	72,55	2,17	2,34	1,33	2,01

Table 6.2 - Durations of activities estimated by the proposed activity classification method designed for a single IMU

Table 6.3 shows the difference of total durations of activities estimated by a commercial physical activity assessment device and our proposed activity classification method that uses single IMU. A positive value means that the physical activity assessment device estimated the total duration more than our proposed method. All the values are given in minutes.

Normal acquisition has approximately 16 hours of activity data (excluding the time for sleep) and the values in table 4 are less than 2 minutes, which means that the output of our proposed method provides data comparable to a proven commercial physical activity assessment device.

Table 6.4 shows the difference of cycle durations and stride lengths estimated between the physical activity assessment device estimates and our proposed system.

[min]		SITTING	STAND	WALK	STEP-UP	STEP-DOWN	StSi	SiSt
OLDER	MEAN	0,87	1,08	-1,24	-0,26	0,06	-0,12	-0,17
	STD	1,55	2,49	1,46	0,46	0,35	0,19	0,33
YOUNG	MEAN	0,84	0,36	-0,79	0,10	-0,09	0,01	-0,07
	STD	0,98	0,92	1,01	0,49	0,29	0,25	0,20
OVERALL	MEAN	0,85	0,70	-1,00	-0,07	-0,02	-0,05	-0,11
	STD	1,26	1,84	1,24	0,50	0,32	0,23	0,27

Table 6.3 – The difference of the total durations of the daily activities estimated by a commercial physical activity assessment device and our proposed activity classification method. All the values are in minutes

		Cycle Durations Difference [s]			Stride Lengths Difference [m]		
		Left Stride	Right Stride	Both	Left Stride	Right Stride	Both
OLDER	MEAN	0,00	-0,01	0,00	-0,03	-0,02	-0,02
	STD	0,03	0,03	0,03	0,03	0,02	0,03
YOUNG	MEAN	-0,02	-0,02	-0,02	-0,04	-0,02	-0,03
	STD	0,03	0,03	0,03	0,03	0,03	0,03
OVERALL	MEAN	-0,01	-0,01	-0,01	-0,03	-0,02	-0,03
	STD	0,03	0,03	0,03	0,03	0,03	0,03

Table 6.4 – Difference between gait cycle durations and stride lengths estimated by physical activity assessment device and our proposed method. Values are given in seconds for cycle durations and in meters for stride lengths

6.3 A Sports Application

The study presented in this thesis also applied on a sports application. The projects aim was to analyze the fitness levels of volleyball players by monitoring their daily life activities. Twenty subjects participated (aged between 18 and 35 years), who were practicing the sport of at least three consecutive years and train at least three times a week. The subjects carried the IMU for 24 hours. Data were acquired using a single IMU (FreeSense, Sensorize®) featuring a tri-axial accelerometer and two bi-axial gyroscopes (sampling frequency 50 Hz). Data collection for the software testing was performed on 20 subjects. Early in the morning, the IMU was placed on the subjects at the waist level and data acquisition started. Then subjects continued their daily life routines carrying the IMU. They were advised to turn off and remove the device before going to bed. The day after the IMU was picked up from the subjects'

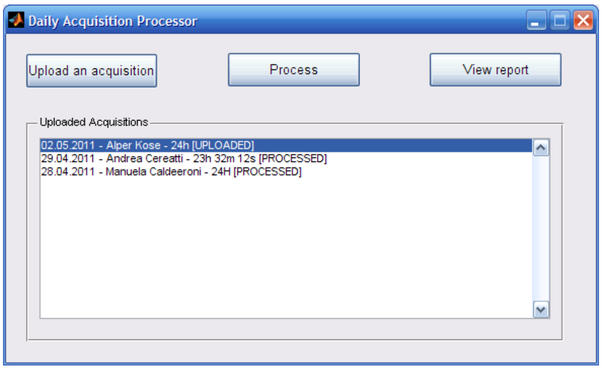

Figure 6.1 – Simple interface to be used to analyse the acquisitions

facilities and the acquired data were transferred to a computer and processed. A software interface was developed that was aimed to be simple and user friendly(Figure 6.1 and 6.2)

The table 6.5 and 6.6 shows the output of the presented methods for the sports applicaiton. The results were used with laboratory data to evaluate the athletes performance.

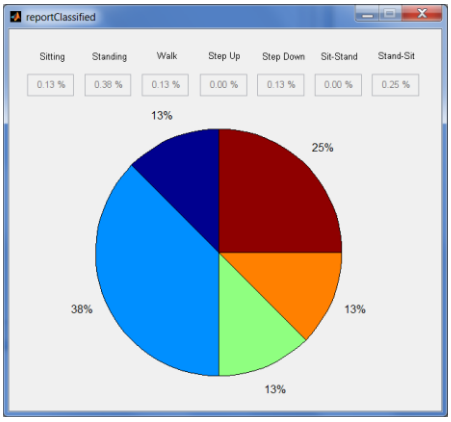

Figure 6.2 – A sample report for an acquisition

	ACTIVITIES						
Athlete	**SITTING (%)**	**STAND (%)**	**WALK (%)**	**STEPUP (%)**	**STEPDOWN (%)**	**StSi (%)**	**SiSt (%)**
1	67,73	21,66	10,02	0,02	0,39	0,09	0,09
2	33,1	51,14	14,92	0,42	0,17	0,12	0,14
3	60,24	30,32	8,09	0,35	0,19	0,4	0,4
4	67,38	25,47	6,39	0,12	0,3	0,19	0,16
5	60,01	31,61	7,56	0,23	0,24	0,14	0,21
6	64,57	25,07	8,71	0,47	0,3	0,44	0,44
7	29,37	51,8	17,94	0,1	0,31	0,23	0,25
8	44,94	42,16	11,89	0,23	0,37	0,19	0,22
9	67,01	26,2	5,97	0,31	0,27	0,12	0,12
10	53,96	36,2	7,63	0,54	0,39	0,62	0,66
11	70,89	22,92	5,43	0,2	0,18	0,19	0,18
12	69,79	20,42	8,88	0,22	0,31	0,18	0,19
13	69,93	20,6	8,97	0,09	0,19	0,12	0,1
14	53,67	31,26	13,73	0,41	0,26	0,32	0,34
15	55,2	29,69	14,2	0,28	0,23	0,22	0,19
16	63,18	30,15	5,51	0,27	0,3	0,29	0,3
17	64,18	26,76	7,69	0,46	0,14	0,38	0,4
18	38,95	48,35	11,86	0,25	0,2	0,2	0,19
19	75,44	20,37	3,75	0,06	0,13	0,1	0,14
20	56,3	35,56	6,81	0,25	0,41	0,31	0,37
Average	**58,29**	**31,39**	**9,30**	**0,26**	**0,26**	**0,24**	**0,26**

Table 6.5 – The percentages of activites performed during the acquisition day by each athlete

	GAIT PARAMETERS		
	AVG SPEED (m/sec)	AVG CADENCE (steps/min)	AVG STRIDE LENGHT (m)
1	1,15	105,80	1,42
2	1,19	94,10	1,83
3	1,19	99,90	1,59
4	1,12	103,50	1,49
5	1,13	96,70	1,58
6	1,34	123,80	1,82
7	1,11	112,90	1,29
8	1,13	101,60	1,50
9	1,18	103,20	1,57
10	1,17	108,10	1,38
11	1,16	110,00	1,40
12	1,03	93,80	1,47
13	1,23	117,60	1,41
14	1,00	100,40	1,34
15	1,35	109,20	1,64
16	1,30	113,30	1,53
17	1,14	99,30	1,62
18	1,31	98,60	1,83
19	1,53	121,50	1,69
20	1,13	103,10	1,58
MEDIA	**1,19**	**105,82**	**1,55**

Table 6.6 – The gait parameters requested in the project for each athlete.