Proceedings of the RAAD 2013
22nd International Workshop on Robotics in Alpe-Adria-Danube Region
September 11-13, 2013, Portoroz, Slovenia

Wearable Sensory System for Robotic Prosthesis

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Abstract. The paper presents a wearable sensory system aimed at tracking of motion parameters and estimation of kinematic data of the wearer for use in controlling active lower-limb ortho-prostheses. The sensory system comprises inertial and magnetic measurement units (IMUs) attached to body segments and sensorized insoles worn inside sneaker shoes. Through sensory fusion, the IMUs data is used to produce estimates of segment orientations, while the insoles provide information on vertical ground reaction force amplitude and distribution. The paper outlines the principles of the algorithms and show the evaluation of them. Algorithms use both reference and wearable sensory data to extract information about the subject's kinematics, movement type and phase and track selected biomechanical stability descriptors. The paper discusses preliminary experimental results of the proposed algorithms.

Keywords. Wearable sensors, Active prosthesis, Sensory fusion, Movement identification, Phase segmentation, Stability tracking

1. Introduction

Loss of a lower-limb can be a great obstacle in the life of persons following lower-limb amputation. It may affect the person's general health. Amputation can be performed at different levels, such as foot level, knee level or at the level of the thigh. Above-knee amputation is usually the most stressful (Hagberg and Brånemark, 2001) of amputation types as it greatly diminishes the person's natural area of movement. Persons following amputation tend to consume more metabolic energy than healthy persons and require greater level of mental effort to move their body without falling (Miller et al., 2001). The goal of the EU-funded CYBERLEGs project (The CYBERnetic LowEr-Limb CoGnitive Orto-prosthesis) is aimed at development of a robotic, wearable ortho-prosthesis. Since currently available passive and active prostheses do not greatly diminish effort and energy consumption, the aim of the project is the development of a cognitive robotic system for persons following above-knee amputation that enables them to perform previously demanding movement maneuvers with minimal mental effort and energy consumption. The maneuvers of interest are steady-state ground-level walking, stair ascent and descent as well as sit-to-stand and stand-to-sit movement.

Laboratory of Robotics at the Faculty of Electrical Engineering, University of Ljubljana is involved in development of a wearable sensory system, sensory fusion, cognitive decision making and intention detection algorithms alongside tracking of stability parameters during movements.

In laboratory environment, systems used for assessment of kinematics parameters are usually based on an optical principle with the use of passive (Vicon) or active markers (Optotrak) (Kirtley, 2006). Such laboratory systems have high accuracy but they are large, expensive, stationary, and have limited measurement space. Recently, the use of inertial and magnetic sensor for assessment of human kinematics parameters has become a common practice (Bonato, 2003; Roetenberg et al., 2009). Inertial sensors are less accurate compared to laboratory systems, however they are lighter, cheaper, wearable and do not alter natural movement patterns. As such they can also be used outside the laboratory environment.

Fusion of sensory signals from inertial and magnetic sensors placed on body segments is used to assess the segments' orientation. Kalman filtering is a common approach for this task, where orientation is estimated by integrating angular velocity (Sabatini, 2006; Yun and Bachmann, 2006). Due to the drift of integrated gyroscope output and temperature dependency, the orientation error tends to grow with time. To compensate for the error of integration, the integrated orientation estimate is fused with the orientation estimate obtained from accelerometer and magnetometer data.

The sensory system, via sensory fusion algorithms, should provide the cognitive system with information on the user's kinematic parameters while the cognitive system provides information about the user's current movement state and intention to the controller. Additionally, tracking of stability parameters should be incorporated into the cognitive system, in order to provide a basis for decisions on reactive movement when a sudden loss of balance is imminent.

This paper is divided into four parts that comprise the cognitive system of CYBERLEGs and build upon each other. The first section describes the wearable hardware used for extracting information on user movement and intention as well as body kinematic parameters. The second part describes the principles upon which the sensory fusion and extraction of kinematic parameters are based and also provides some preliminary evaluation data of the proposed algorithms. Based on sensory data, part three presents a cognitive machine that identifies current movement maneuver that user is performing and classifies phases within that particular movement type. The system provides data on steady states as well as transitions between these states. Furthermore, part four describes tracking of independent particular stability descriptive parameters are tracked based on a statistical anthropometric model, estimated kinematic parameters and directly measured sensory information.

2. Wearable sensory system hardware

The CYBERLEGs sensory and feedback system uses commercially-available components and custom-made sensing components, developed within the CYBERLEGs Consortium (see schematic shown in Figure 1). As the figure shows, the system comprises several wearable sensors - sensorized insoles, pressure-sensitive pads to measure human-robot interaction, inertial measurement units (IMUs), vibrotactile modules for afferent feedback and sensors for detection of amputee psychophysiological stress status - in addition to sensors for controlling the actuation system and measurement of the joint positions of the ortho-prosthesis. Communication with the main controller employs both UDP and SPI protocols, while sensory fusion runs on a separate real-time OS (xPC Target) based machine. The inertial measurement units are used for assessing the orientation of human body segments, and shoe insoles for measuring ground reaction forces. The sensory data acquisition unit consists of two wireless receiver units (RU) for fetching data via 802.15.4 (ZigBee) and Bluetooth protocols. Transfer of acquired data employs Ethernet UDP communication to the controller that runs the tools for data processing and sensory fusion algorithms.

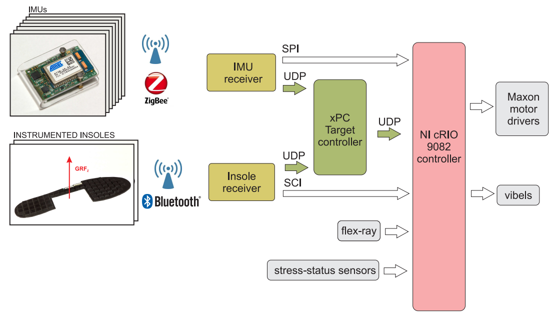

Figure 1. CYBERLEGs wearable sensory system: sensors and data acquisition unit

2.1. Sensorized insoles

The CYBERLEGs pressure-sensitive insoles, developed at Scuola Superiore Sant' Anna, Pisa, Italy (De Rossi et al., 2011), comprise an array of 64 pressure sensors and fit into normal sneaker shoes. Each cell has a working range from 0 to 70 N. They are wireless, run on battery power and output vertical ground reaction force estimate as well as a distribution of this force along the sole (Center of Pressure).

2.2. Inertial measurement system

An inertial and magnetic measurement unit (Figure 2) consists of three sensors which measure 3D vectors of angular velocity (range $\pm 500\,^\circ/\mathrm{s}$), translational acceleration (range $\pm 2\,\mathrm{G}$), and magnetic field (range $\pm 1.3\,\mathrm{Ga}$) and is equipped with an onboard 8-bit processor (Beravs et al., 2011). The size of the IMU without the battery is $30 \times 20 \times 5$ mm. For measuring kinematic parameters of the human body, seven IMUs are used. Each of the IMU is placed on an individual segment of lower extremities: feet, shanks, thighs, and trunk. Placement of the IMU on the segment is determined with initial evaluation of IMU orientation during standstill.

3. Assessment of kinematic parameters

Kinematics of the human body can be estimated using data provided by wearable sensors. Based on sensory signals from seven IMUs, we have developed an algorithm for kinematics parameters assessment by means of sensory data fusion.

A common approach for determining segment orientations is the use of an Unscented Kalman filter applied to the measurement data (Beravs et al., 2011). The approach is based on individual segment's angular velocity integration during motion and orientation correction with respect to gravity and the Earth's mag-

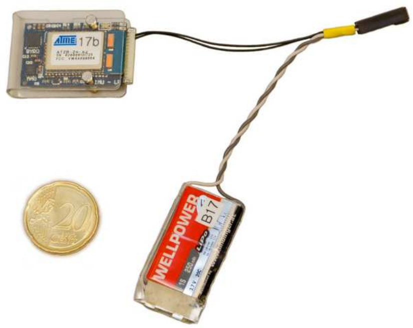

Figure 2. Inertial measurement unit with a battery.

netic field. The accelerometer is used as an inclinometer by comparing measured acceleration vector to the vector of gravity in order to determine the intermediate angle of inclination. For successful implementation of the magnetometer into the algorithm it is assumed that magnetic field in space is locally constant (constant direction and length) and non-parallel to gravity. Considering this assumption, the angle of rotation around the gravity vector can be calculated by comparing the measured magnetic vector with the initial vector of the magnetic field. The approach often results in a drift during long-term dynamical movement due to gyroscope drift, errors introduced by separation of gravity and dynamic acceleration, and changes of the magnetic field. To compensate for this effect, resetting during standstill was introduced. In order to further reduce the drift without the need for standstill, a kinematic model of the human body was incorporated into the sensory fusion algorithm.

To determine joint angles that describe relative position between segments, an error quaternion between two adjacent segments is calculated and presented with rotation angles as shown in Figure 3.

Other parameters which can also be obtained with the presented wearable system (e.g. step duration, gait frequency, acceleration of centers of mass, ...) exceed the scope of this paper.

4. Movement classification and phase detection

In literature, authors presented segmentations for different movement types: ground-level walking (Whittle, 1996), walking over obstacles (Li et al., 2012) , stair climbing (McFadyen and Winter, 1988), sit-to-stand and stand-to-sit (Kralj et al., 1990). A threshold-based decision tree was developed for performing recognition of ground level walking with gait phases, stair ascent and descent and stand-to-sit and sit-to-stand maneuver based on wearable sensory data. In

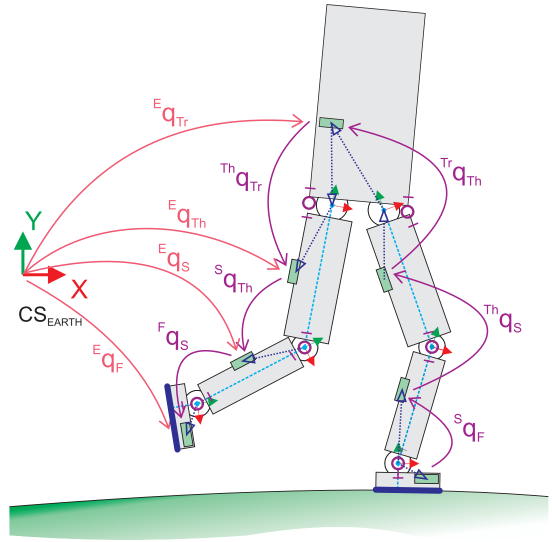

Figure 3. Calculation of body kinematic parameters

Figure 4 a conceptual state diagram with all the possible transitions between detected maneuvers and gait phases is presented.

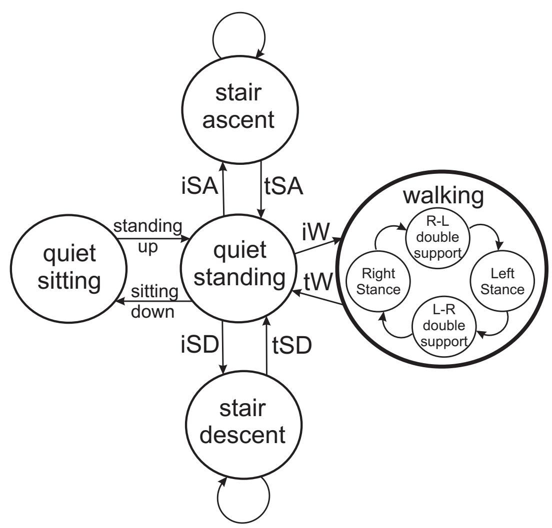

Figure 4. A conceptual diagram of the detected set of movement types and transitions; iW - initiation of walking; iSA - initiation of stair ascent; iSD - initiation of stair descent; tW - termination of walking; tSA - termination of stair ascent; tSD - termination of stair descent

The decision tree was tuned off-line to perform movement identification and intention detection as well as phase segmentation within recognized maneuvers. The algorithm was tested with healthy subjects online, in real-time. Results show that while this approach is successful for recognition of movement types, it is sensitive to unexpected behavior. For this reason, a more robust, state-machine architecture for the algorithm was built. This approach allows transitions between states to occur only when they satisfy a number of specific conditions. The transition threshold values may be defined manually while specific conditions and the general order of magnitude of these values remain unchanged. On the other hand, this makes the classification and segmentation machine less tailored to a specific wearer of the sensory system.

As an alternative, a fuzzy logic approach was utilized. The approach resulted in creating soft (fuzzy) transition rules for the state-machine with the use of fuzzy clustering method. The method outputs probability with which the fused sensory data best fits a given signal cluster (Gagula-Palalic, 2008). The centers of each cluster were taught before-hand, offline. Probability is calculated as the distance to each of the centers.

5. Tracking of balance descriptors

The human body is a multi-body system, supported by only one or two relatively small segments, which results in a fairly small supportive polygon. This polygon is a convex hull that includes all points of contact between the body and the outside world. Human posture is defined by reciprocal relationships of human-body segments and their orientation with respect to the Earth's inertial frame. One of the goals of the CYBERLEGs project is to track estimates of particular balance descriptors using only data derived from wearable sensors.

Two balance descriptors were chosen for tracking: the whole body Center Of Mass (COM) and the Zero-Moment Point (ZMP - a point on the ground where the horizontal components of the resultant moment are equal to zero).

The COM is determined from kinematic parameters of the user and warrants knowledge of mass and inertial parameters of particular segments of the human body. Thus, the segmental COM positions are estimated according to segment orientations and statistically-determined human body anthropometrical data (De Leva, 1996). The ZMP can either be measured (when the resultant horizontal moment is balanced) or estimated from a combination of kinematic and inertial data. The derivation of ZMP through forward kinematics is based on moment equilibrium in the ground plane, following equation (1) (Dekker, 2009):

$$\begin{aligned} M_R = [0\,0\,M_{Rz}]^T = \\ \sum_{i=1}^{n}(r_{\vec{COM},i} \times (m_i \cdot \vec{a}_i) + \\ I_i \cdot \dot{\omega}_i + \omega_i \times (I_i \cdot \omega_i)) - \\ r_{\vec{COM}} \times m_{body} \cdot \vec{g} + \\ (\sum_{i=1}^{n} m_i \cdot \vec{a}_i - m_{body} \cdot \vec{g}) \times \vec{r}_{ZMP}. \end{aligned} \quad (1)$$

The index i denotes the i-th segment, m mass, ω and $\dot{\omega}_i$ angular velocity and acceleration, respectively. I_i is the segments inertia matrix, while $\vec{r}_{COM,i}$ and $\vec{r}_{ZMP}$ denote vectors of segment COMs (former) and ZMP (latter).

The proposed algorithms build upon assumptions, which introduce some limitations to the accuracy of the estimates. They assume that all body segments are non-compliant, the ground is rigid and level and no sliding or slipping occurs. Furthermore, all anthropometric and kinematic information is assumed known (Dekker, 2009).

6. Experimental evaluation

Experimental data was collected in experiments with multiple subjects performing walking, stair climbing and sit-to-stand maneuvers. Using NDI Optotrak 3D optical position measurement system, spatial positions of active infrared markers, attached to bony landmarks of the subject's body, were measured. Linear and angular velocities as well as accelerations were either derived from 3D position data (only dynamic acceleration) or directly measured by the inertial measurement units, placed on the subject's body segments. In the latter case, each IMU was equipped with three IR markers, relaying information on placement position and orientation to the investigators. During the walking maneuver, data from sensorized insoles was collected in order to determine foot-ground contact times and estimates of vertical ground reaction force and center of pressure. Two IR markers were positioned at the side of the shoe soles to estimate (with knowledge of the sole outline with respect to these markers) the contact hull of support for each foot. Sensor placement is shown in Figure 5. Experimental validation of the wearable system for measuring movement kinematics of healthy subjects was performed by comparison of orientations obtained from IMUs with data acquired by the Optotrak system.

6.1. Detection of walking phases

Initial testing and validation was performed for the walking maneuver. Figure 6 shows results of online recognition for the walking maneuver with gait phases using a hard-coded state-machine and fuzzy clustering method. Results of preliminary comparison show

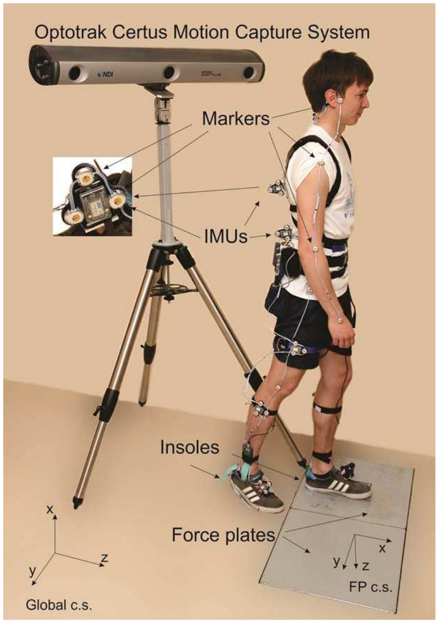

Figure 5. Experimental evaluation: reference system (Optotrak Certus Motion Capture System and Force plates) and wearable sensors (IMUs and Insoles)

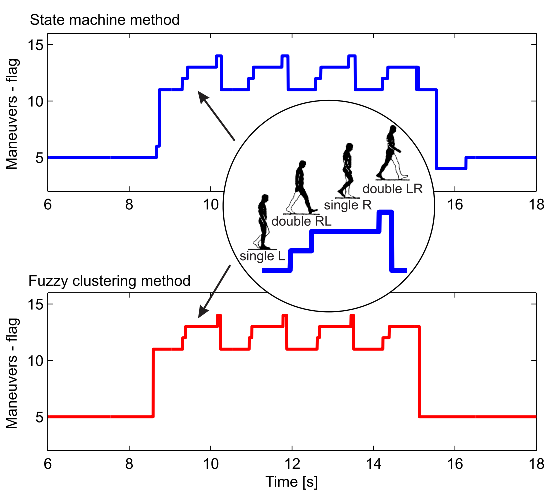

Figure 6. Results of maneuvers and gait phases detection comparing two different approaches (above: state machine, bellow: fuzzy logic clustering)

more robust performance of the state-machine algorithm, while fuzzy logic offers easier adjustments to an individual subject. Currently, the fuzzy clustering method requires the clusters to be defined offline, based on a learning set, before applying them to the classification and segmentation engine.

6.2. Motion kinematics tracking in standing-up

Experimental validation of the wearable system for measuring movement kinematics of healthy subjects was performed by comparison of joint angles obtained from IMU with data acquired by a reference measurement system (Optotrak). Joint angles were derived from measured positions of markers placed on bony landmarks of the subject's body. Five IMUs were placed on body segments (shanks, thighs and trunk) along with IR active markers for position reference. Joint angles were obtained with decomposition of error quaternions between two segments. The algorithm was evaluated with experiments in standing-up and sitting-down of a healthy subject. Experimental protocol involved several repetitions of sit-to-stand and stand-to-sit motion during three-minute-long measurements. Typical joint angle trajectories (knee and hip angles and trunk inclination) derived from Optotrak- or IMU-based data, respectively, are presented in Figure 7.

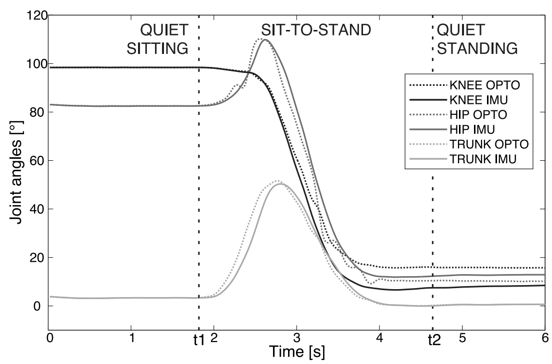

Figure 7. Typical knee and hip angles and trunk inclination during standing up obtained with reference system (OPTO) and wearable system (IMU). Times t_1 and t_2 denote the start and finish of standing up, respectively

Statistical comparison of joint angles (knee and hip joint angle and trunk inclination angle) is presented in Figure 8 with boxplots of absolute error between angles obtained from the Optotrak system and those from the wearable system. Results show that the median value of absolute error of the wearable system is below 2° and is as such appropriate for measuring kinematics parameters.

6.3. Balance descriptors

For the stair climbing maneuver, the trajectories of the ZMP point, measured by the reference force sensors implemented in ground and stairs, were compared to the ZMP trajectory estimated from position-derived data. Seven healthy subjects performed multiple barefoot walks up the stairs. Results showed a combined RMSE error of 54 mm, thus proving the concept of

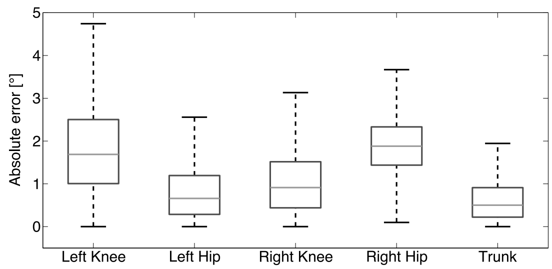

Figure 8. Boxplot of absolute error between joint angles calculated from IMUs data and angles calculated from Optotrak data

ZMP assessment by a kinematics-based approach for a human subject in motion (Ambrozic, 2012).

An algorithm that combines data provided from position sensors with data, collected by wearable sensors, was used to yield sample-based balance descriptor estimates with respect to a desired coordinate frame origin. Estimates of COM and ZMP trajectories from combined sensory data for a 4-step walking maneuver are shown in Figure 9.

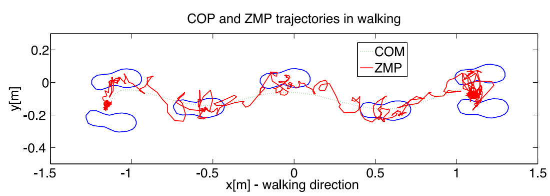

Figure 9. ZMP and COM trajectory w.r.t. feet support for a 4-step walking maneuver with quiet standing at the beginning and end of walk

Preliminary results indicate that balance descriptors estimated from a combination of sensors are equally descriptive as those derived solely from position data. In addition, by combining subject kinematics with data from the insoles, we are able to track the instantaneous base of support. As a result, the ZMP stability margin (minimal distance from the edge of the support polygon) can be assessed on-line. Figure 10 shows one slow walk with 4 steps, starting and ending while the subject is in quiet standing. Stability is quantified as the distance from the closest point in which the resultant moment on the body, acting in the plane of the ground support, can be balanced by a resultant force applied to the ground by the subject. Depending on whether this point lies within the base of support or outside of it, the point is termed ZMP or Fictitious ZMP, respectively. The distance from the closest edge of the support polygon is positive when the resultant force should be applied outside and negative when inside the instantaneous base of support. Preliminary investigation suggests that most

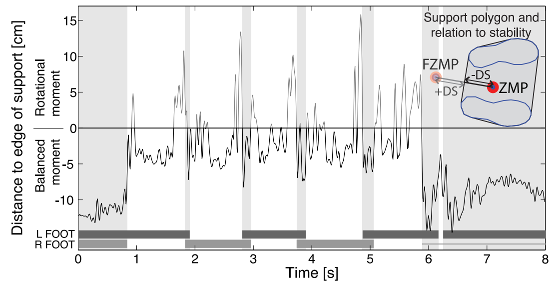

Figure 10. Assessed stability in terms of minimal distance of the ZMP from the edge of support polygon. Negative values denote situations where the ZMP point lies within the base of support while positive values convey the distance of the FZMP (a point outside the support polygon) to the edge of the base of support. The bottom lines show contact times of the left and right foot, respectively. Grey patches over the entire figure mark double support instances, while white space marks single stance

of the unbalanced moment (tipping about the edge of support) is present at times of beginning and end of single support - that is right after toe off and right before heel strike of the swing leg. This conforms with the idea that humans take advantage of physical dynamics of the body during steady-state gait with regard to swing foot placement (Matthis and Fajen, 2013) and react to unbalanced moment by moving parts of the body that are not in contact with the environment and thus maximize stability (Robert et al., 2009).

7. Conclusions

This paper presents the sensory system for robotic ortho-prosthesis which is based on wearable sensors incorporating the inertial measurements units and sensorized insoles worn by the subject. Data from the wearable system is fused by sensory fusion algorithms to assess the human body motion kinematics, identify motion maneuver and its phases, and track stability descriptors.

The algorithm for motion kinematics assessment is based on Extended Kalman filtering and fuses the integral of angular velocity with the estimate of linear acceleration, based on kinematic model of the human body. Experimental validation of the algorithm was accomplished on healthy subject performing sit-to-stand maneuver. Comparison of joint angles, assessed by wearable system, with those obtained from reference position measurements results in absolute error median smaller than 2°. The results confirm the suitability of wearable system for joint angles assessment in dynamic situations. Additionally, performance on detection of maneuvers and gait phases was tested online, exploiting both measured and estimated data. Two different algorithms were developed and evaluated. A decision tree with threshold based rules generally performs more robust detection, while the fuzzy clustering method is more convenient when the acquisition of training data sets is possible. Furthermore, fuzzy clusters can be tailored to each subject. Making use of a statistical anthropometric model, segmental centers of mass and the estimated ZMP position, the support polygon was assessed and the ZMP stability margin quantified for ground level walking. Results suggest that most of the unbalanced moment (tipping over the edge of support) is present at instants of beginning and end of single support phase. This suggests that humans take advantage of physical dynamics of the body during steady-state gait, thus exhibiting globally stable gait.

In future developments, the presented contributions will be combined to form a unique sensory system for motion parameters tracking based on wearable sensory data only.

8. Acknowledgements

The CYBERLEGs project is financed within the scope of the 7th framework of the European Community (FP7/2007-2013) under grant number 287894. This study was partially supported by the Slovenian Research Agency (ARRS) under contract number 1000-11-310147.

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