2013

Wavelet Based Automated Postural Event Detection and Activity Classification with Single IMU (TEMPO)

Thurmon E. Lockhart
Virginia Tech

Rahul Soangra
Chapman University, soangra@chapman.edu

Jian Zhang
Virginia Tech

Xuefang Wu
Virginia Tech

Follow this and additional works at: https://digitalcommons.chapman.edu/pt_articles

Part of the Musculoskeletal System Commons, and the Physical Therapy Commons

Recommended Citation

Bibliography
Lockhart, T. E., Soangra, R., J. Zhang, and X. Wu. "Wavelet based automated postural event detection and activity classification with single IMU (TEMPO)." In *Biomedical Sciences Instrumentation*, vol. 49, pp. 224-33. Research Triangle Park, NC: International Society of Automation, 2013. PMID: 23686204
Note
T. E. Lockhart, Soangra, R., J. Zhang, and X. Wu, "Wavelet based automated postural event detection and activity classification with single IMU (TEMPO)," in *Biomedical Sciences Instrumentation*, vol. 49 (Research Triangle Park, NC: International Society of Automation, 2013), 224-33. PMID: 23686204

Wavelet Based Automated Postural Event Detection and Activity Classification with Single IMU (TEMPO)

Wavelet based automated postural event detection and activity classification with single IMU (TEMPO)

Thurmon E. Lockhart, **Rahul Soangra**, **Jian Zhang**, and **Xuefang Wu**

Abstract

Mobility characteristics associated with activity of daily living such as sitting down, lying down, rising up, and walking are considered to be important in maintaining functional independence and healthy life style especially for the growing elderly population. Characteristics of postural transitions such as sit-to-stand are widely used by clinicians as a physical indicator of health, and walking is used as an important mobility assessment tool. Many tools have been developed to assist in the assessment of functional levels and to detect a person's activities during daily life. These include questionnaires, observation, diaries, kinetic and kinematic systems, and validated functional tests. These measures are costly and time consuming, rely on subjective patient recall and may not accurately reflect functional ability in the patient's home. In order to provide a low-cost, objective assessment of functional ability, inertial measurement unit (IMU) using MEMS technology has been employed to ascertain ADLs. These measures facilitate long-term monitoring of activity of daily living using wearable sensors. IMU system are desirable in monitoring human postures since they respond to both frequency and the intensity of movements and measure both dc (gravitational acceleration vector) and ac (acceleration due to body movement) components at a low cost. This has enabled the development of a small, lightweight, portable system that can be worn by a free-living subject without motion impediment - TEMPO. Using the TEMPO system, we acquired indirect measures of biomechanical variables that can be used as an assessment of individual mobility characteristics with accuracy and recognition rates that are comparable to the modern motion capture systems. In this study, five subjects performed various ADLs and mobility measures such as posture transitions and gait characteristics were obtained. We developed postural event detection and classification algorithm using denoised signals from single wireless inertial measurement unit (TEMPO) placed at sternum. The algorithm was further validated and verified with motion capture system in laboratory environment. Wavelet denoising highlighted postural events and transition durations that further provided clinical information on postural control and motor coordination. The presented method can be applied in real life ambulatory monitoring approaches for assessing condition of elderly.

INTRODUCTION

In the coming next two decades about 20% of US population will be above the age of 65 years (U.S. Census bureau) and their cost of healthcare will add 25% to the overall healthcare in the US (CDC 2010). In 2009, about 2.2 million nonfatal fall injuries were reported among older adults and were treated in emergency departments and more than 581,000 of these patients were hospitalized[1]. Also, in the year 2007, over 18,000 older adults died from fall injuries [1]. A recent survey by Liberty mutual research institute for safety ranks falls as the second leading cause of disabling injury and number of falls remain at same level since last decade and costs about $8.37 billion each year. Falls are due to

postural imbalance and locomotion impairment, and cause of serious hazards to the elderly, which has lately become a public research interest [2, 3]. In spite of the multiple efforts aiming to decrease the high mortality and improve the quality of life in the elderly, limited success has been achieved. While reducing fall accident experienced by all older adults is a major public health challenge, it is especially crucial for keeping the elderly functionally independent. Increased fall rates of the elderly, if addressed, could dramatically decrease morbidity and mortality in this growing population.

Home health care and telemedicine have been looked upon as possible health and activity monitoring solution for this growing elderly population.

Postural control has been defined as positional control of the whole body in space for purpose of balance and orientation [4]. Postural orientation is an ability to maintain appropriate relationship between body and body segments and is dependent upon goals of movement task and environmental context [5]. Human postural control is highly governed by vestibular, visual, proprioceptive inputs, and integrated central processing [6–8]. The background level of muscle tone activity changes in certain antigravity postural muscles when we counteract force of gravity. This increased level of activity in antigravity muscles is known as postural tone. Visual inputs and vestibular systems are known to influence postural tone in various muscles while transition movement occurs (e.g., sit to stand). However, postural adjustments associated with movement are called anticipatory postural adjustments (APAs) and are preplanned by CNS and serve to counteract the perturbation to postural control induced during the movement activity[9]. In other words, prior to voluntary limb movement, APAs serve to maintain postural stability by compensating for destabilizing forces associated with moving a limb [5] and thus prepare sensory and motor systems for postural demands based on previous experience and learning. The CNS combines independent though related muscles into units called muscle synergies, which are constrained to act together as a unit, thus reducing the control demand on CNS. Although it is unknown how at higher levels CNS manages APAs to optimize postural stability in movements, but at lower level changes in postural strategies articulated by postural demand of a task (stand-to-sit, sit-to-lay and other daily activities) can be quantified and investigated with inertial measures of involved limbs. This measure is indicative of the final response of neuromuscular system. Many researchers have related postural control with understanding of balance, motor control and gait problems in elderly population[4]. Postural motor control delay coupled with lower extremity strength degradation in elderly can lead to difficulty in maintaining balance upon a postural perturbation and may increase the risk of falls.

Presently, clinical assessment tools used are questionnaires, observation, diaries, kinetic and kinematic systems, and validated functional tests. "Timed get-up and go" method [10] has been widely used as a standard feature of clinical tests of elderly mobility, although it has sit-to-walk movement, gait and turning as separate components but their respective transition times cannot be identified from the single time value score. Characteristics of postural transitions such as sit-to-stand are widely used by clinicians as a physical indicator of health, but transitions such as sit-to-(stand)-walk have been identified as inherently more unstable than just sit-to-stand movements [11]. Sit-to-walk movement has been used as a functional task that challenges balance and coordination[12]. Walking is used as an important mobility assessment tool to determine the extent of neurological disorders [13]. Measurement of temporal events in gait cycle such as heel contact and toe-off information of double support duration may alert physician to the inability of the patient to compensate for progressive weakness, and thus enable early consideration of surgical or orthotic treatment [14]. Duration of double support phase during gait cycle reflects stability during gait [14] and fallers are found to have increased stride to stride variations in double support time [15].

Although modern motion capture laboratories, collect precise gait and posture data but are expensive and immobile, limiting their capabilities for continuous, long-term data collection in natural settings. As a result, gait researchers have had limited success achieving accurate fall risk assessment in diverse elderly patient population. Also, laboratory and clinical measurements are time consuming often unrealistic in busy clinical environments, while relying on subjective patient recall may not accurately reflect functional ability in the patient's home environment. Major limitations of most observational gait and posture analysis are poor reliability even among highly experienced clinicians. However, this work addresses these limitations by developing and validating a custom-designed inexpensive wearable wireless sensor (TEMPO) system that collects accurate and precise gait and posture data continuously and non-invasively, and objectively of functional ability, and can readily be employed to ascertain ADLs [16–18].

Pathological changes in postural transition patterns and changes in postural transition duration can be used as an indicator of health status [16]. The use of IMU reduces the human source of error in postural timing events. We have tested concurrent validity of IMU based system measuring time events and transition phases in sit-to-stand postural movements against those taken from three-dimensional motion capture system. IMU sensors can be used beneficially in telemedicine to analyze movements of the elderly person and detect distress situations such as balance loss and falls providing timely care. Wavelet denoising of IMU signals highlighted postural events and transition durations that further provided clinical information on postural control and motor coordination. Moreover, IMU/ TEMPO can be efficiently used in monitoring of an individual's daily movements and provide information regarding movement frequencies and intensities, and can lead to better diagnosis of postural instabilities and assessments of falls risk in the environment and situations in which their own living environments.

METHODS

Sensors

The IMU system is based on the TEMPO 3.1 system which is manufactured in collaborative research with inertia team in UVA [17]. It consist of MMA7261QT tri-axial accelerometers and IDG-300 (x and y plane gyroscope) and ADXRS300 as z-plane uniaxial gyroscope. The data acquisition was carried using a bluetooth adapter and Laptop through a custom built LabView VI [17]. (Figure 1 a).

Description

Data are acquired with sampling frequency of 128Hz. This frequency is largely sufficient for human movement analysis in daily activities which occurs in bandwidth [0.8–5Hz] (for a sensor on upper extremity of body)[18]. The collected data is stored in custom xml file using the custom built LabView VI and the battery consumption of TEMPO node has been reduced by entering in sleep mode when waiting for acquisition.

Positioning

The IMU acquisition circuit is kept immobile on the subject's body and worn in a pocket at sternum (Figure 1 a & b). This position is chosen for its comfort in wearing the device for a long duration without hindrance to natural activities, and more importantly, trunk movements are helpful in detecting postural changes.

Signal Processing Of Inertial Sensors

In order to support the clinical decision making, IMU signal must be clearly represented and filtered, and to remove noises and artifacts from the signal. IMU signals are non-stationary

and need denoising, and an efficient technique for non-stationary signal processing is the wavelet transform. The wavelet transform can be used as a decomposition of a signal in the timefrequency scale plane.

WAVELET DENOISING

Wavelets are used for the processing of signals that are non-stationary which are time varying in nature. In wavelet transform, the original signal is transformed using a selected mother wavelet. Using pilot hit and trial testing of various mother wavelets we figured out that daubechies family wavelet (db10) were beneficial in highlighting postural events. In discrete case like ours the wavelet transform is modified to filter bank tree structure using the decomposition / reconstruction at level 5. Basically, decomposition of the signal into the basis of wavelet functions implies the computation of the inner products between the signal and the prototype functions, leading to a set of coefficients called wavelet coefficients. The signal can consequently be reconstructed as a linear combination of the prototype functions weighted by the wavelet coefficients. But here in our denoising protocol we have set all detail coefficients to zero and carried on reconstruction of the signal. Thus, only the approximation coefficients are used in an inverse wavelet transformation to reconstruct the data-set. The mother wavelet $\psi(t)$ is defined as

$$\psi(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} g(k)\phi(2t - k)$$

Where the wavelet coefficients

$$g(k) = (-1)^k h(1 - k)$$

And the scaling function

$$\varphi(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} h(k)\varphi(2t - k)$$

Where h(k) are the scaling coefficients. The wavelet transform represents the decomposition of a function into a family of wavelet functions. Three simple steps of denoising algorithm that used in the wavelet transform are *Step 1*. Calculate the wavelet transform of the noisy signal; *Step 2*. *Discard* the noisy wavelet detail coefficients; *Step 3*. Compute the inverse transform using the approximation coefficients. A Matlab routine was created using Mallat's algorithm of discrete wavelet transform[19]. Raw and denoised signals are shown in Figure 2 b.

WALKING DETECTION

Moving window median were used on denoised gyro-y and gyro-z and walking threshold was established. Median windows helped in removing short postural transitions such as stand-to-sit, sit-tostand, sit-to-lay, lay-to-sit etc. from the dynamic events such as walking (Figure 3).

LAY DOWN DETECTION

Lay down event was classified when detected dynamic events had acc-z greater than 0.5g and acc-y less than 0.5 g. This threshold was used as major gravity component shifts from sensitive y-direction to sensitive z-direction of IMU when lying in supine posture.

SIT/STAND EVENT DETECTION

Sit-to-stand events and stand-to-sit events were classified as those dynamic events which were neither classified as walking nor as lay down. This was done by replacing the data interval where walking and lay down events occurred by calibration data points and using the static threshold in truncated acc-z and truncated gyro-x.

EXPERIMENT

POSTURAL EVENTS DETECTION—A robust algorithm to detect postural events occurring in daily life of an individual without any user-specified parameters was deployed. Testing total of five subjects (2 females, 3 males, mean age: 28) in our Locomotion Research Laboratory at Virginia Tech, and data was collected for seven minutes continuously with sampling rate of 128Hz – simulating various ADLs to test protocol to evaluate the classification algorithm.

The experimental procedures were explained to all participants and informed consent was obtained individually before the experiment. The participants performed common daily activities– walking, standing upright/sitting down and laying down on a bed with one IMU/ TEMPO node attached at the sternum as shown in the Figure 1. Data obtained was denoised using db10 (daubechies family) mother wavelet at level 5 and, all details were left during reconstruction using MATLAB (R2010a Mathworks Ltd). Denoised data was then used in analysis of posture events detections utilizing a posture classification algorithm (Figure 3). Figure 5 illustrates time in seconds of each posture that was maintained (e.g., participants stood for 120 seconds, walked for 360 seconds, stood for 20 seconds, etc.), and identifications of postural transitions were made using the "gold standard" baseline data (i.e., known/true postures) with measured postural data using the motion capture system. Classification accuracy was ideal for standing, walking, and laying down postures, however, transitional aspects of postures (i.e., stand-to-sit and sit-to-stand) were more difficult to classify perfectly. Since then, we've developed a method for accurately determining the postural transitions utilizing a gyroscope (illustrated in Figure 4).

GAIT AND MOBILITY PARAMETERS—After the classification procedure (see activity event detection and classification section), gait and mobility parameters such as the double support time and postural transition durations are calculated using the methods below.

Double support is a part of stride when both feet are in contact with the ground. To illustrate, Trunk Gyro- X (trunk angular velocity with flexion/extension) signals during standing, walking and various other postures during seven minute activity is illustrated in Figure 4-a. A 3-seconds walking data from sternum TEMPO is denoised and Heel Strike and Toe Off events are identified (Figure 4-b). In order to synchronize motion capture system and the IMU/TEMPO, two TEMPO (IMU) nodes were used. One of the TEMPO nodes was at sternum and another TEMPO sensor was mounted on the right wrist of the subjects. An infra-red marker was placed on wrist near TEMPO node. Camera system and floor embedded force plates were used to obtain kinematics and kinetics of the lower extremity during gait on the walking platform. Participants were asked to tap quickly near the right wrist and start walking on a walkway. This was conducted in order to synchronize the TEMPO signals with the wrist infra-red marker acquired using motion capture camera which were used to temporally synchronize the IMU data with force plates by a custom built

LabView VI. Double support time information was computed from the duration between heel strike by the contacting foot and toe-off by the contralateral foot. The trunk vertical accelerations represented the whole body COM transitional acceleration occurring shortly after the heel strike event [20]. Postural transition times included initial flexion phase-t1, mid-transition phase-t2, and late extension phase-t3 (postural durations =sum of all phases). These postural transition time delays can be interpreted as an indicator of pathology in coordination of involved postural muscles to perform the postural task.

RESULTS

We have developed a wireless one-node gait/mobility assessment system. Additionally, a robust algorithm to detect postural events associated with ADLs were developed and tested in quantifying fall risk associated with gait instability. The results indicated that the sensitivity of our algorithm was 96.78 %, with specificity at 92.31% (False Negative =18, False Positive =17, True Negative =204, True Positive=541 from 15 records of five participants).

DISCUSSION AND FUTURE WORK

Two factors of gait and postural characteristics, which are relevant to balance control and dynamic stability during ambulation, are: double-support time and postural transition times [21, 22]. In terms of the biomechanical principle, increased double support time is indicative of gait adaptation to improve stability, and longer postural transition duration is indicative of pathology or weakness leading to increased fall propensity [23]. Additionally, an increase in the variability of one or both of these parameters in elderly at any time could indicate lack of compensation for instability and may predispose an individual to falls, especially when balance mechanisms are stressed [24]. Temporal (double support time) and transitional aspects of postures over several walking cycles and transition events were used to assess and differentiate gait and mobility decrements. Collection of these variables could allow more useful comparisons to assess the effects of elderly pathological conditions and frailty on gait characteristics relevant for fall risks at their home. Furthermore, postural transitions as proxy for functional mobility status can be developed. Postural transition parameter is considered to be important since movements from sit-to-stand and rising from a lying position were among the most common activities associated with daily life and the most mechanically demanding functional tasks in daily activities [25, 26]. Additionally, older adults fall more often during these transitions. Monitoring of postural transitions using the TEMPO and computing the duration to further evaluate the increased fall risks in this population is warranted (i.e., increased postural transition duration – e.g., "slow to get out of the chair" and "unable to rise from a chair of knee height without using the arms" is indicative of degraded functional status and increased fall propensity)[27]. Furthermore, in order to veer away from traditional way of analyzing postures visually, we propose to denoise IMU signals using Mallets method such that signals can highlight postural events and associated postural temporal phases. Thus using TEMPO system, we can successfully measure biomechanical variables that can assess individuals mobility characteristics with high accuracy that are comparable to the motion capture laboratories.

Acknowledgments

References

1. CDC. Centers for Disease Control and Prevention. Center for Injury Prevention and Control; 2010.

2. Maki BE, Holliday PJ, Topper AK. Fear of Falling and Postural Performance in the Elderly. Journals of Gerontology. 1991 Jul.vol. 46:M123–M131. [PubMed: 2071833]

3. Ohtaki Y, Sagawa K, Inooka H. A method for gait analysis in a daily living environment by body-mounted instruments. Jsme International Journal Series C-Mechanical Systems Machine Elements and Manufacturing. 2001 Dec.vol. 44:1125–1132.

4. Woollacott M. Attention and the control of posture and gait: a review of an emerging area of research. Gait & Posture. 2002; vol. 16:1–14. [PubMed: 12127181]

5. Horak FB. Postural orientation and equilibrium: what do we need to know about neural control of balance to prevent falls? Age Ageing. 2006 Sep; vol. 35(Suppl 2):ii7–ii11. [PubMed: 16926210]

6. Allum JH, Bloem BR, Carpenter MG, Hulliger M, Hadders-Algra M. Proprioceptive control of posture: a review of new concepts. Gait Posture. 1998 Dec 1.vol. 8:214–242. [PubMed: 10200410]

7. Carpenter MG, Allum JH, Honegger F. Vestibular influences on human postural control in combinations of pitch and roll planes reveal differences in spatiotemporal processing. Exp Brain Res. 2001 Sep.vol. 140:95–111. [PubMed: 11500802]

8. Colebatch JG. Consequences and assessment of human vestibular failure: implications for postural control. Adv Exp Med Biol. 2002; vol. 508:105–110. [PubMed: 12171099]

9. Hall LM, Brauer S, Horak F, Hodges PW. Adaptive changes in anticipatory postural adjustments with novel and familiar postural supports. J Neurophysiol. 2010 Feb.vol. 103:968–976. [PubMed: 19955284]

10. Podsiadlo D, Richardson S. The Timed up and Go - a Test of Basic Functional Mobility for Frail Elderly Persons. Journal of the American Geriatrics Society. 1991 Feb.vol. 39:142–148. [PubMed: 1991946]

11. Magnan A. Modification of the sit-to-stand task with the addition of gait initiation. Gait & Posture. 1996; vol. 4:232–241.

12. Kerr A, Rafferty D, Kerr KM, Durward B. Timing phases of the sit-to-walk movement: Validity of a clinical test. Gait & Posture. 2007 Jun.vol. 26:11–16. [PubMed: 16908153]

13. Pearson OR, Busse ME, van Deursen RWM, Wiles CM. Quantification of walking mobility in neurological disorders. Qjm-an International Journal of Medicine. 2004 Aug.vol. 97:463–475. [PubMed: 15256604]

14. Khodadadeh S, Mcclelland MR, Nene AV, Patrick JH. The Use of Double Support Time for Monitoring the Gait of Muscular-Dystrophy Patients. Clinical Biomechanics. 1987 May.vol. 2:68–70. [PubMed: 23915646]

15. Verghese J, Holtzer R, Lipton RB, Wang CL. Quantitative Gait Markers and Incident Fall Risk in Older Adults. Journals of Gerontology Series a-Biological Sciences and Medical Sciences. 2009 Aug.vol. 64:896–901.

16. LeBellego G, Noury N, Virone G, Mousseau M, Demongeot J. A model for the measurement of patient activity in a hospital suite. IEEE Trans Inf Technol Biomed. 2006 Jan.vol. 10:92–99. [PubMed: 16445254]

17. Barth AT, Hanson MA, Powell HC Jr, Lach J. TEMPO 3.1: A Body Area Sensor Network Platform for Continuous Movement Assessment. 2009:71–76.

18. Bouten CV, Koekkoek KT, Verduin M, Kodde R, Janssen JD. A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity. IEEE Trans Biomed Eng. 1997 Mar.vol. 44:136–147. [PubMed: 9216127]

19. Mallat SG. A Theory for Multiresolution Signal Decomposition - the Wavelet Representation. Ieee Transactions on Pattern Analysis and Machine Intelligence. 1989 Jul.vol. 11:674–693.

20. Lockhart TE, Woldstad JC, Smith JL. Effects of age-related gait changes on the biomechanics of slips and falls. Ergonomics. 2003 Oct 10.vol. 46:1136–1160. [PubMed: 12933077]

21. Nelson AJ, Certo LJ, Lembo LS, Lopez DA, Manfredonia EF, Vanichpong SK, et al. The Functional Ambulation Performance of elderly fallers and non-fallers walking at their preferred velocity. Neurorehabilitation. 1999; vol. 13:141–146.

22. Parijat P, Lockhart TE. Effects of quadriceps fatigue on the biomechanics of gait and slip propensity. Gait & Posture. 2008 Nov.vol. 28:568–573. [PubMed: 18514522]

23. Robinovitch SN, Heller B, Lui A, Cortez J. Effect of strength and speed of torque development on balance recovery with the ankle strategy. Journal of Neurophysiology. 2002 Aug.vol. 88:613–620. [PubMed: 12163514]

24. Hausdorff JM, Mitchell SL, Firtion R, Peng CK, Cudkowicz ME, Wei JY, et al. Altered fractal dynamics of gait: Reduced stride-interval correlations with aging and Huntington's disease. Journal of Applied Physiology. 1997 Jan.vol. 82:262–269. [PubMed: 9029225]

25. Kralj A, Jaeger RJ, Munih M. Analysis of Standing up and Sitting down in Humans - Definitions and Normative Data Presentation. Journal of Biomechanics. 1990; vol. 23:1123–1138. [PubMed: 2277047]

26. Baer GD, Ashburn AM. Trunk Movements in Older Subjects during Sit-to-Stand. Archives of Physical Medicine and Rehabilitation. Sep.1995 vol. 76:844–849. [PubMed: 7668956]

27. Campbell AJ, Borrie MJ, Spears GF. Risk-Factors for Falls in a Community-Based Prospective-Study of People 70 Years and Older. Journals of Gerontology. 1989 Jul.vol. 44:M112–M117. [PubMed: 2738307]
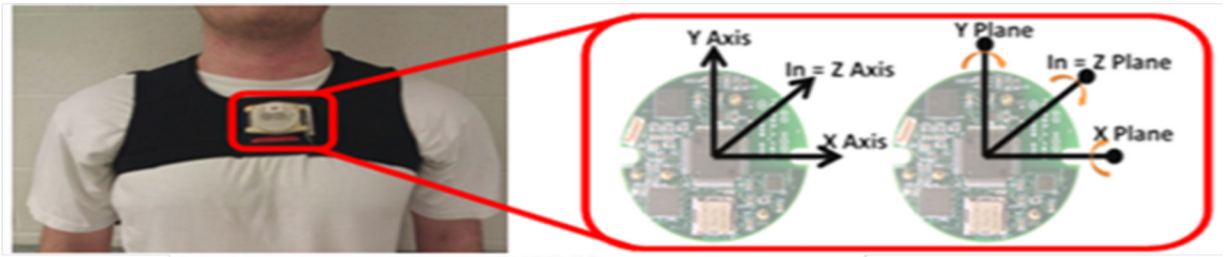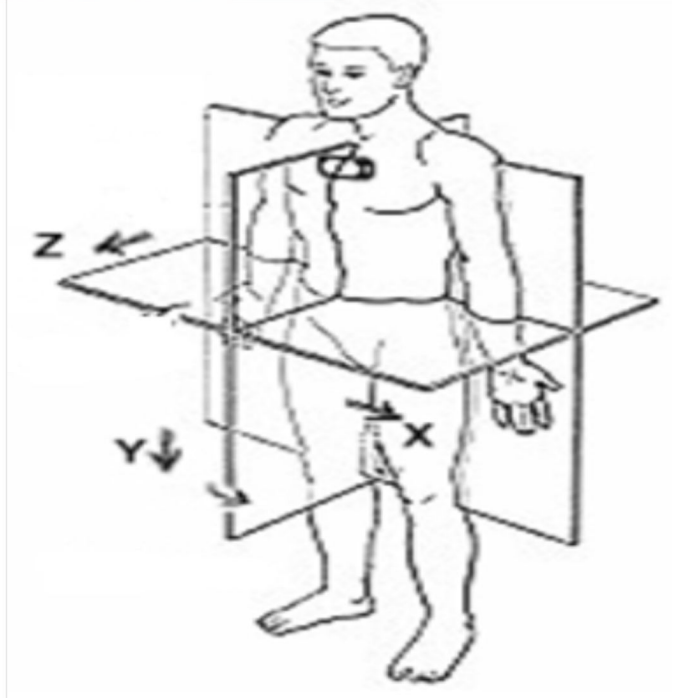
Figure 1.
a) TEMPO node providing six degrees of freedom motion capture in a form factor which can be attached at sternum level b) Sensitive axis's of IMU
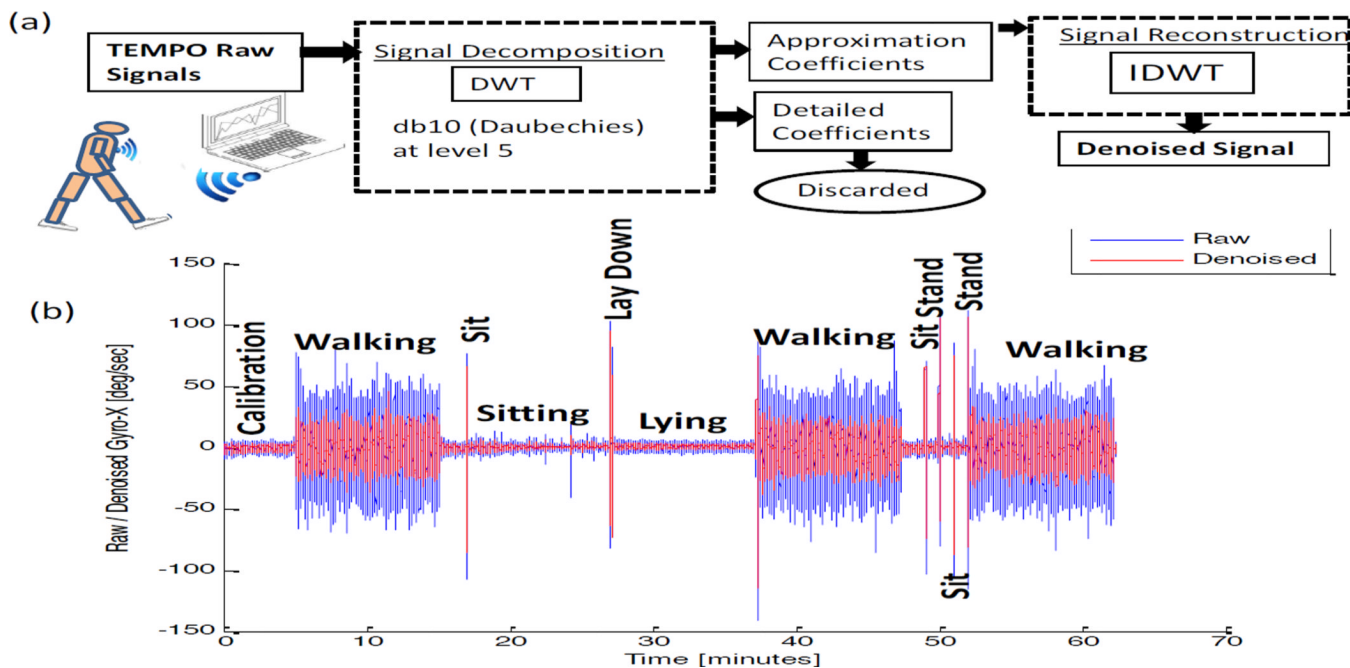
Figure 2.
a) Schematic diagram of denoising method b) Gyroscope signals for daily activities in raw (blue colored) and denoised (red colored) collected for an hour duration
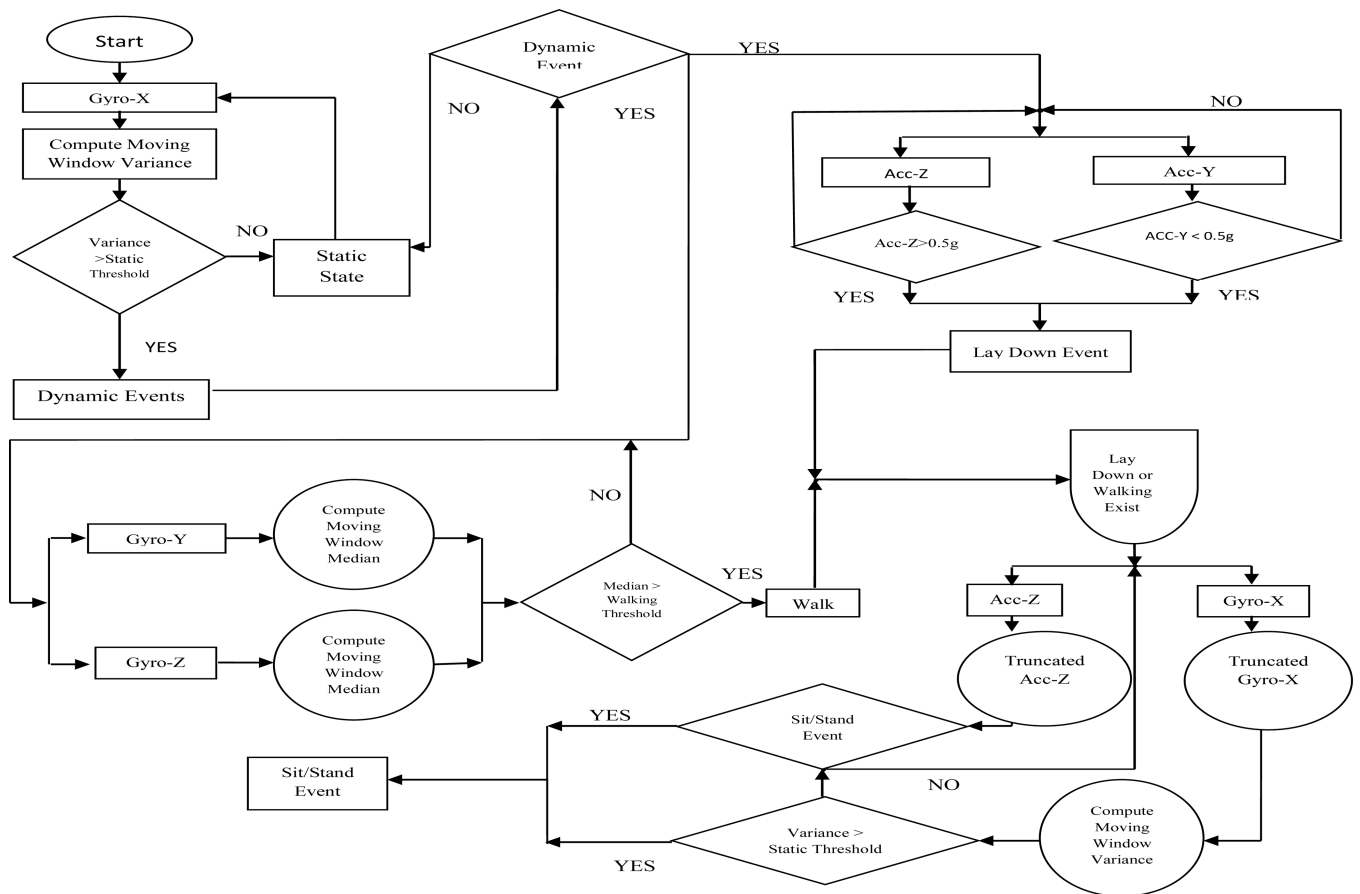
Figure 3.
pseudo code for postural event identification and further classification into static, dynamic, walking, laydown and sit/ stand.
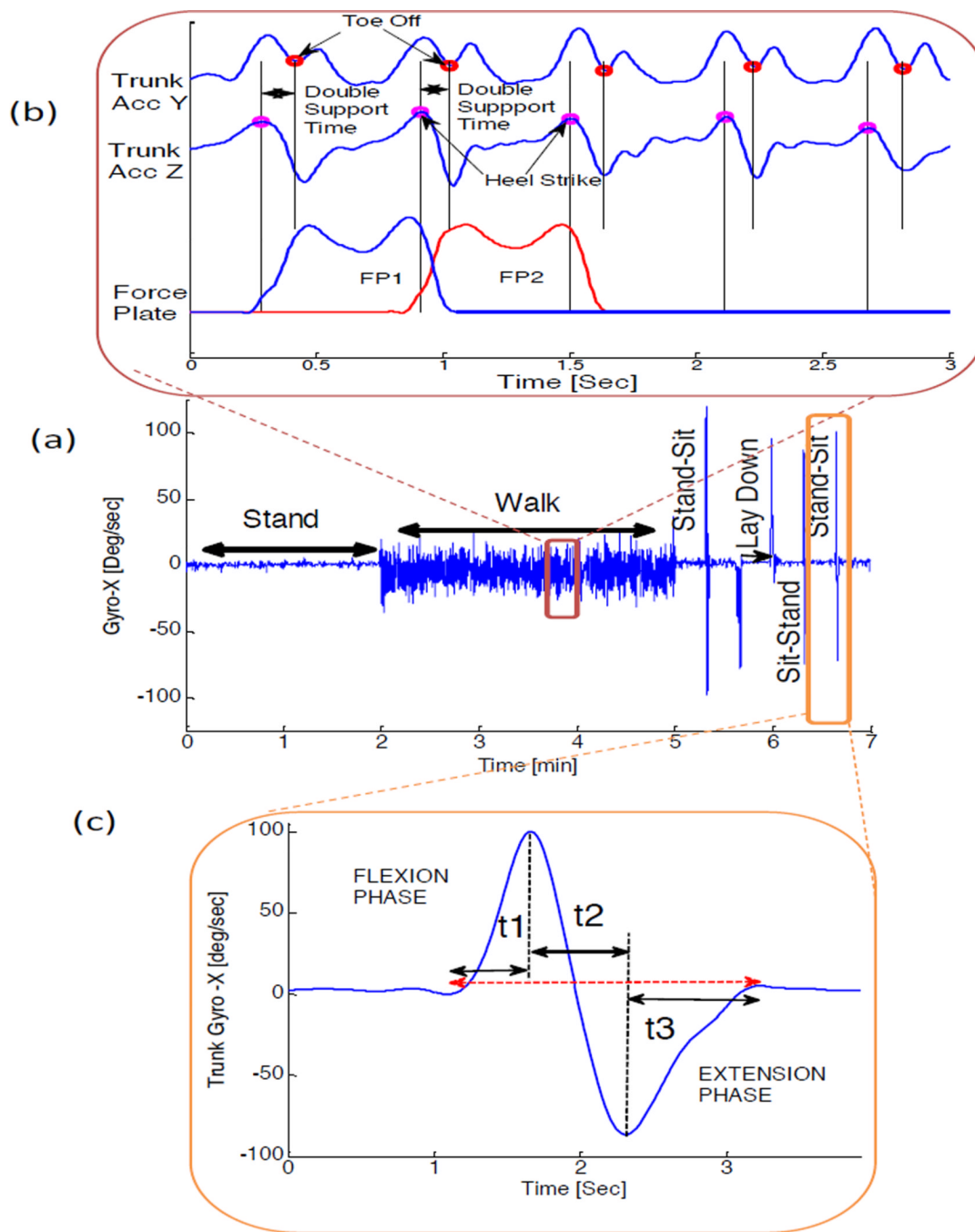
Figure 4.
Illustration of time epochs associated with calculating the gait and mobility parameters using the TEMPO including the ground reaction forces (GRF) a) Gyro-x denoised signals illustrating various activities b) walking signals synchronized with camera and force plates : illustrate heel strike events by trunk acc-z and trunk acc-y showing toe-off events, furthermore double support temporal information is gathered c)sit-to-stand posture transition is illustrated by gyro-x denoised signals and flexion phase time t1, mid-transition phase time t2, and trunk flexion phase time t3

Figure 5.
Sequence of performed postural transitions and their durations. Different postural transitions involved are shown with different color.
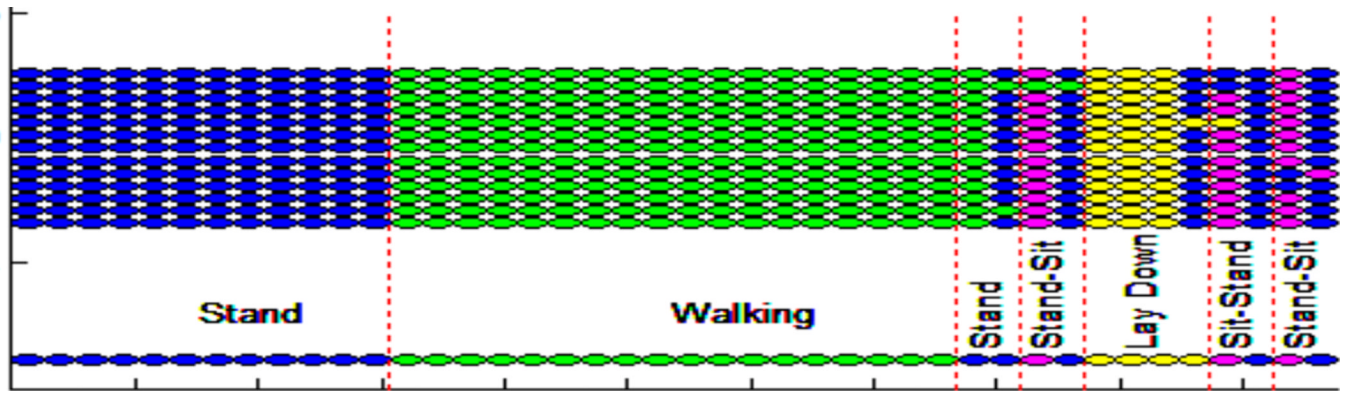
Figure 6.
Bead diagram of identified posture with 'gold standard' baseline data at bottom.