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Continuous Monitoring of Functional Activities using Wearable, Wireless Gyroscope and Accelerometer Technology

Robert C. Wagenaar, Inbal Sapir, Yuting Zhang, Stacey Markovic, Lucia M. Vaina, and Thomas D.C. Little

Abstract- **The development of functional activity monitors (FAMs) will allow rehabilitation researchers and clinicians to evaluate treatment efficacy, to monitor compliance to exercise instructions, and to provide real time feedback in the treatment of movement disorders during the performance of daily activities. The purpose of the present study was to develop and test a small sized wearable FAM system comprised of three sensors positioned on the sternum and both thighs, wireless Bluetooth transmission capability to a smartphone, and computationally efficient activity detection algorithms for the accurate detection of functional activities. Each sensor was composed of a tri-axial accelerometer and a tri-axial gyroscope. Computationally efficient activity recognition algorithms were developed, using a sliding window of 1 second, the variability of the tilt angle time series and power spectral analysis. In addition, it includes a decision tree that identifies postures such as sitting, standing and lying, walking at comfortable, slow and fast speeds, transitions between these functional activities (e.g, sit-to-stand and stand-to-sit), activity duration and step frequency. In a research lab setting the output of the FAM system, video recordings and a 3D motion analysis system were compared in 10 healthy young adults. The results show that the agreement between the FAM system and the video recordings ranged from 98.10% to 100% for all postures, transfers and walking periods. There were no significant differences in activity durations and step frequency between measurement instruments.**

I. INTRODUCTION

Functional decline with aging increases the risk of disability, dependency, falls, and mortality [1] [2]. Hence, there is growing interest in rehabilitation and the development of function promoting anabolic therapies (FPTAs) for the treatment and prevention of aging-associated functional limitations [3]. In addition, very limited information is available on how rehabilitation and FPATs affect the levels of functional activities (e.g., walking, stair climbing, running, biking, etc.) in the home and community based setting. It has been argued that functional activities in the home environment are excellent integrated measures of physical function and that there is a pertinent need for the development of reliable, valid and responsive measures for the assessment of the (reduced) level of activity in the evaluation of older individuals participating in clinical trials and home care services [4].

Currently, questionnaires, video recordings and pedometers are used in the assessment of functional activities in the home and community based setting [5]. As a result of limitations of these measurement instruments, there is a strong interest in the technology of Micro Electro Mechanical Systems (MEMS) that allowed for the development of miniature and low powered inertial sensors such as accelerometers and gyroscopes, in the continuous measurement of functional activities. Most applications in clinical research involve the usage of one or two accelerometers attached to ankle and/or wrist (e.g., pedometers). The limitation of this configuration is that only (frequency of) walking periods, steps per minute and global level of activity can be accurately assessed [6]. Other sensor configurations have been tested, but showed limited capability of detecting different postural and locomotion activities [7] [8] [9]. Previous studies by our research group has demonstrated that walking, sitting and standing periods lasting longer than 5 seconds in the home and community based setting can be accurately assessed for at least 24 hours with one activity monitor on the sternum and one on both thighs [10]. The limitations of current activity monitor designs include the maximal hours of date recording, energy supply, the extraction of recorded data, the size of the data-logger attached to the body, the algorithms used in data-reduction and the assessment of other functional activities such as sitting, standing, lying, transfers and walking. The introduction of wireless communication techniques and smartphones eliminates these barriers and will allow rehabilitation researchers and clinicians to 1) evaluate treatment efficacy, 2) monitor compliance to exercise instructions, and 3) provide real time feedback in the treatment of movement disorders during the performance of the relevant daily activities.

Previous research has demonstrated that accelerometers are less accurate when the angles of rotation are large. Gyroscopes appear to be more reliable in the measurement of angles [11], and, therefore, can more accurately identify functional activities and the emerging movement patterns. With the implementation of Kalman filters, wavelet transforms and neural networks the occurrence of drift in the gyroscope time series has been significantly reduced [13]

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R.C. Wagenaar is with College of Health and Rehabilitation Sciences at Boston University, Boston, MA 02215 USA (phone: 617 353-7533; e-mail: wagenaar@bu.edu).

I. Sapir is with College of Health and Rehabilitation Sciences at Boston University (e-mail: ssinbal@bu.edu).

Y. Zhang is with College of Engineering at Boston University (email: zhangyuting.hust@gmail.com)

S. Markovic is with College of Engineering at Boston University (e-mail: markovic@bu.edu).

L.M. Vaina is with College of Engineering at Boston University (e-mail: vaina@bu.edu).

T.D.C. Little is with College of Engineering at Boston University (e-mail: tdcl@bu.edu).

[14] [15]. However, these algorithms are complex and cannot be easily implemented on the FAM as a result of computational power and energy demands on the smartphone. In addition, it has been argued that the combination of different technologies (e.g., gyroscope and accelerometers) provides the most optimal activity monitor platform [12].

The specific aim of the present study was to develop and test a small sized wireless FAM system that can accurately record functional activities in the home and community based setting. It was hypothesized that the FAM system comprised of 3 sensors positioned on the sternum and the two thighs, wireless Bluetooth transmission to a smartphone, and computational efficient activity detection algorithms will allow for the accurate identification of postures (sitting, standing and lying), walking (at comfortable, slow and fast speeds) and transfers between activities as well as activity duration and step frequency.

II. MATERIALS AND METHODS

A. Subjects

Ten healthy young adults (5 females and 5 males) included in the study were 18-30 years of age and had no walking disability or complicating medical history. They all gave informed consent, and the study was approved by the Boston University Institutional Review Board.

B. Methods

During the experiment the subjects were instructed to walk over ground a distance of 10 meters at a comfortable, slow and fast speed, and to maintain a sitting, standing and lying down position for 20 to 60 seconds. Each trial included multiple postures, transfers and walking periods. Anthropometric measures such as body mass and height and leg length (from greater trochanter to lateral malleolus on the ankle) were obtained, using a balance scale with a height rod and a measuring tape. The experiment was carried out in the Clinical Movement Sciences Laboratory at Boston University.

C. Instrumentation

1) Functional Activity Monitor (FAM): The FAM is comprised of three IMU 6 degree of freedom sensors, version 4 (V4; Sparkfun Inc, Boulder CO, USA), which were positioned on the sternum and both thighs. Each sensor included one tri-axial accelerometer (Freescale, MMA7260Q) and one tri-axial gyroscope (InvenSense, Idg500, 500 degree/second), and was powered by 3.7V lithium ion batteries. The sensitivity of the accelerometer was set at 1.5g to save energy and battery life. All sensors transmitted signals wireless by means of Bluetooth to a smartphone (Motorola Inc.). The sampling rate was set at 50 Hz.

2) 3D motion recording system: Three dimensional (3D) kinematic data was collected by means of the Optotrak 3020 system (Northern Digital Inc., Waterloo, ON, Canada). Three Optotrak Position Sensors each consisting of a bank of three cameras were positioned around the subject to allow for 3D movement recording, and calibrations were accepted when the mean calibration error was 0.7 mm or less. Infrared light emitting diodes (IREDs) were attached bilaterally to the ankle (lateral malleolus), knee (lateral femoral condyle), hip (Iliac crest), and shoulder (clavicle anterior surface). In addition, IREDs were placed on each FAM. The sampling rate was set at 100Hz.

3) Video cameras: One HDC video camera, model HS100P/PC (Panasonic Inc.) and one HD video camera, model VIXIA HG21(Canon Inc.) stationed on tripods were used for video recordings. The sampling rate was 30Hz.

D) Data reduction and analysis

1) FAM time series: Pitch (ρ) is defined as the angle of the x-axis relative to the ground, Roll (φ) is defined as the angle of the y-axis relative to the ground and Theta (θ)) is defined as the angle of the z-axis relative to the ground [16]. The accelerometer signal was filtered, using a second-order forward-backward digital low-pass Butterworth filter at a cutoff frequency at 3 Hz. The angles of the sternum and both thighs were estimated from the accelerometer time series by applying the following arctangent function:

$$AccAngle = \arctan\left(g_z / \sqrt{(g_x2 + g_y2)}\right)$$

The gyroscope signal was filtered by means of a median-mean filter designed to eliminate burst noise and outlier signals. Subsequently, a complementary filter and a calibration procedure using the accelerometer time series were applied to eliminate drift observed in the gyroscope time series (see Fig. 1).

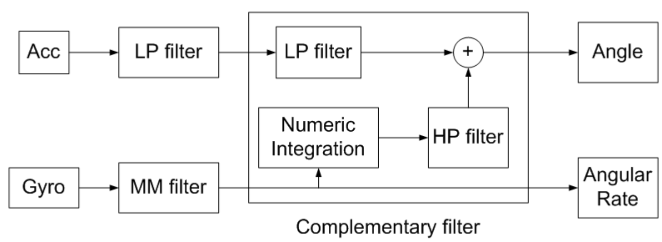

Figure 1. Signal processing flow: Complementary filter and calibration procedure. Acc represents the acceleration time series, Gyro the gyroscope time series, LP filter the lowpass filter, HP the highpass filter and MM the median-mean filter.

The angular rate data was integrated to angles by means of the equation $\theta = \int\omega dt + \theta_0$. The sternum and thigh angles were adjusted to the difference between absolute vertical zero angle (obtained via wall calibration) and a specific tilt angle depending on the subject's body shape and posture in the anatomical posture (obtained via personal calibration). The outcomes of our instrumentation reliability studies using a Digital Angle Protractor (Denali) showed that the difference in mean static angles between the FAM system and the Optrotrak system ranged from minimally 0.26º to maximally 1.18º with a mean difference of 0.57º and SD of 0.92º for five fixed angles (0º, 30º, 60º, 90º and 120º). Using a Biodex system (SEMI, Toronto,ON) we imposed amplitudes of 120º, 90º, 60º, 30º and 5º at four different frequencies 80,60, 40, 20 bits/min and found a difference of minimally 0.06º to maximally 2.3º with a mean value of 0.61º and SD of 0.188º. These findings demonstrate a high accuracy for both static and dynamic angles.

In order to differentiate between activities, the standard deviation (SD) of the complete acceleration time series in the z axis for all three sensors was calculated for each 1 second interval [7]. A SD threshold of 2º was applied to distinguish between static activities (e.g., sitting, standing and lying) and dynamic activities (e.g., transfers and walking). The specific ranges for trunk and thigh angles were used to identify sitting (sternum -20º to 20º and thighs 25º to 110º), standing (both sternum and thighs -20º to 20º); and lying (sternum -130º to -50º and thighs 50º to 130º). If no postures were identified, the posture was labeled "unidentified static activity" (see Fig. 2). When the 1st second of dynamic activity was detected, the algorithm counted the number of peaks from the gyroscope time series of the chest sensor. If the number of peaks was less than or equal to 3 and the maximum angle difference from the mean angle of last second of "static" activity was greater than 20°, the activity was identified as a transfer. If the number of peaks was greater than 3, the algorithm estimated the power spectrum density (PSD) of the chest sensor time series to identify the step frequency. If the step frequency fell in the range of 0.5-3Hz [17], the activity was identified as walking. If the frequency detected was not within that range, the algorithm labeled the activity as "unidentified dynamic activity". The algorithm's output included the sequence of activities, the duration of each activity (in seconds), and if activity was identified as walking, the PSD estimate of step frequency.

2) Optotrak time series: If there were up to twenty consecutive samples of data missing, the raw time series was interpolated. After interpolation, the data was filtered using a zero-lag, fourth order Butterworth low pass filter with a cutoff frequency of 5 Hz. Stride frequency (SF) was estimated by dividing the number of peaks in the time series of the leg swing angle by the elapsed time, which was dependent on the duration of the walking speed condition. The initial contact of the foot was determined by identifying the time frame at which the antero-posterior component of the velocity of the heel marker changed from a positive to a negative value.

All computations were performed using custom made Matlab programs (The MathWorks, Natick, MA) for the FAM and Optotrak data.

D. Statistical analysis

A cross-tab analysis was applied to evaluate the agreement in detection of activities between the FAM system and the video recordings. An ANOVA with repeated measures was applied to compare the FAM system and the video recordings for the durations of the activities identified.

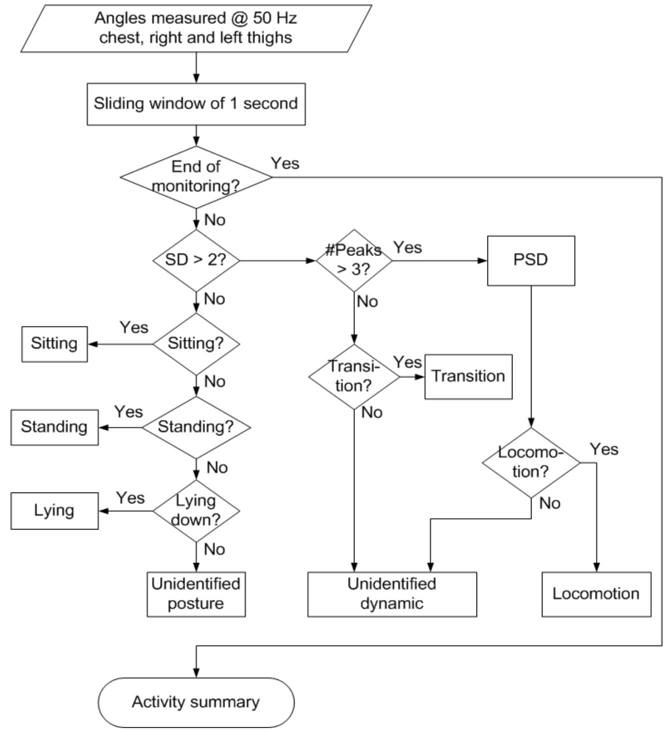

Figure 2. Flowchart activity recognition algorithm.

A significant main effect of Tool (2 levels: FAM and Video) would indicate a difference between the two systems. In a similar approach, an ANOVA with repeated measures was also applied in the comparison of the FAM system and the Optotrak system in determining the step frequency during the walking periods identified. All statistical analyses were carried out with version 18.0 of SPSS statistical software package (SPSS, Inc. Chicago, IL).

III. RESULTS

The agreement between the FAM system and the video recordings ranged from 98.1% to 100% for all postures, transfers and walking. The agreement for the individual activities was 98.1% for standing, 98.6% for sitting, and 100% for lying, transfers and walking (see Fig. 3).

There was no significant difference in the durations of the activities between the FAM system and the video recording ($p=0.69$).

In addition, the comparison between the FAM system and the Optotrak system showed no significant difference in the step frequency across all walking periods at comfortable, slow and fast walking speeds ($p=0.90$). A main effect of Velocity was found ($p<0.001$) with no significant interaction effect between Tool and Velocity ($p=0.85$), indicating that both systems accurately captured changes in step frequency.

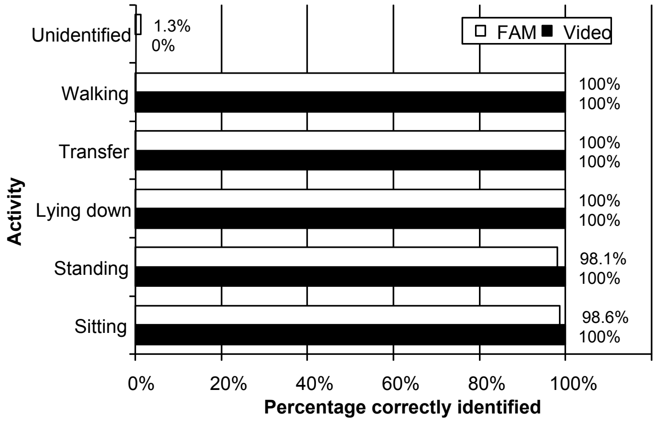

Figure 3: Percentage of correctly identified activities

IV. DISCUSSION

The outcomes of the present study indicate that the FAM system not only accurately identifies functional activities such as sitting, standing, lying, transfers and walking, but it also measures accurately the duration of these activities and step frequency during over-ground walking. The FAM configuration including one sensor on the sternum and one on each thigh, allows for the identification of different functional activities. The implementation of computationally efficient algorithms for measuring angles with the gyroscope calibrated by the accelerometer not only results in an accurate measurement of static and dynamic angles, but also in a highly accurate detection of daily activities. Remarkable is the accurate detection of walking and measurement of the duration of walking periods and step frequency at all walking speeds. Especially the low and fast walking speeds tend to reduce the accuracy of the detection of walking. The outcomes of our previous gait studies on the coordination dynamics of walking using walking speed as a reference have led to optimal gait pattern recognition algorithms [18]. Currently, we are testing the implementation of these algorithms on the smartphone, which will provide the capability of real time online monitoring of functional activities and providing real time instantaneous feedback when movement disorders occur. With the current set-up, the identification of the activities on the PDA takes approximately 196ms processing time. In addition, we are evaluating the reliability of the FAM system in the home and community based setting, and its ability to detect changes in daily activities as a result of, for example, a gait training program (“responsiveness”). We plan to expand the algorithms by implementing neural network approaches, stochastic decision algorithms and machine learning strategies, which will increase our capability to detect daily activities. In addition, we will test different FAM configurations on the body that will allow us to monitor uni-manual and bi-manual (daily) tasks, such as combing and washing hair, washing dishes, throwing balls, etc. Without any modification the FAM system can be applied to individuals with movement disorders as a result of, for example, a stroke or Parkinson’s disease.

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REFERENCES

[1] (CDC), C.f.D.C.a.P., “Falls among older adults: An overview, in National Center for Injury Prevention and Control,”, Department of Health and Human Services, 2009.
[2] (CDC). C.f.D.C.a.P., “Self-Reported Falls and Falls-Related Injuries among persons aged 65> years - United States,” 2006. MMWR, 2008, Vol. 57(9), pp. 225-229, 2008
[3] R.C. Wagenaar, K.G. Holt, M. Kubo, and C-L Ho, “Gait risk factors for falls in older adults: A dynamic perspective,” Generations, Vol 25, pp. 28-32, 2003.
[4] D.K. White, R.C. Wagenaar, T. Ellis, and L. Tickle-Degnen. “Changes in walking activity and endurance following rehabilitation for individuals with Parkinson’s disease,” Arch Phys Med Rehabil, Vol. 90(1), pp. 43-50, 2009.
[5] D.K. White, R.C. Wagenaar, R.C., and T. Ellis. “Monitoring activity in individuals with Parkinson’s disease: A validity study,” J Neurological Physical Therapy, Vol. 30 (1), pp. 12-21, 2006.
[6] Storti, K. L., Pettee, K. K., Brach, J. S., Talkowski, J. B., Richardson, C. R., & Kriska, A. M. Gait speed and step-count monitor accuracy in community-dwelling older adults. Med Sci Sports Exerc, 40(1), 59-64, 2008.
[7] G.M. Lyons, K. M., Culhane, D. Hilton, P.A. Grace, P. A., and D. Lyons, D. A description of an accelerometer-based mobility monitoring technique. Med Eng Phys, 27(6), 497-504, 2005.
[8] B. Najafi, K. Aminian, A. Paraschiv-Ionescu, F. Loew, C.J Bula, and P. Robert. “Ambulatory system for human motion analysis using a kinematic sensor: Monitoring of daily physical activity in the elderly,” IEEE Trans Biomed Eng, Vol. 50(6), pp. 711-723, 2003.
[9] K.M. Culhane, G.M. Lyons, D. Hilton, P.A. Grace, and D. Lyons. “Long-term mobility monitoring of older adults using accelerometers in a clinical environment”. Clin Rehabil, Vol. 18(3), pp. 335-343, 2004
[10] D.K. White, R.C. Wagenaar, M.E. Del Olmo, and T. Ellis. “The test-retest reliability of 24 hours of activity monitoring in individuals with Parkinson’s disease in home and community,” Neurorehabil Neural Repair, Vol. 21(4), pp. 327-40, 2007.
[11] M.C. Boonstra, R.M. van der Slikke, H.L. Keijsers, R.C. van Lummerl, M.C. de Waal-Malefijt, and N. Verdonschot, “The accuracy of measuring the kinematics of rising from a chair with accelerometers and gyroscopes,” J Biomechanics, vol. 39 (2), pp. 354-358, 2006.
[12] H.J. Luinge, P.H. Veltink, and C.T. Baten, “Estimating orientation with gyroscopes and accelerometers,” Technology and Healtcare, pp. 455-459, 1999.
[13] Q. Lui, and J. Teng, “Research of gyro signal de-noise with stationary wavelets transform,” CCECE, pp 1989-1992, 2003.
[14] X. Chen, “Modeling random gyro drift by time series neural networks and by traditional method,” Proc. of IEEE Int Conf Neural Networks and Signal Processing, Nanjing, China, pp. 810-813, Dec. 2003.
[15] A. Plamondon, A. Delisle, C. Larue, D. Brouillette, D. McFadden, P. Desjardins, et al. “Evaluation of a hybrid system for three-dimensional measurement of trunk posture in motion,” Appl Ergon, Vol. 38(6), pp. 697-712, 2007.
[16] K.Tuck. “Tilt sensing using linear accelerometers. Freescale Semi-conductor,” Application Note Rev 2. 2007.
[17] R.C. Wagenaar, and R.E.A. van Emmerik. “Resonant frequencies of arms and legs identify different walking patterns,” J Biomechanics, Vol. 33, pp. 853-861, 2000.
[18] R.C. Wagenaar, and R.E.A. van Emmerik. “Dynamics of movement disorders,” Human Movement Science, Vol. 15, pp. 161-175, 1996.