

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

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## Abstract

Functional decline with aging and the growing interest in interventions aimed at the treatment and prevention of aging-associated functional limitations have resulted in a strong interest in continuous monitoring of daily activities in the home and community setting. 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 computational 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. The 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 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.

**Keywords** – activity monitoring, motion analysis, body area networking, smart phones.

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## 1. 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 an excellent integrated measure of physical function and that there is a pertinent need for the development of reliable, valid and responsive measures for the assessment of (reduced) level of activity in the evaluation of older individuals participating in clinical trials and home care services [4].

Currently, questionnaires and video recording 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 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 date, 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. It has been argued that the combination of different technologies (e.g., gyroscope and accelerometers) provides the most optimal activity monitor platform [12] 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] [14] [15]. However, these algorithms are complex and cannot be easily applied in the FAM as a result of computational power and energy demands on the smartphone.

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 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.

## 2. 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 an informed consent form, 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 measured 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 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. Video recording was collected at a frequency of 30Hz.

### D) Data reduction and analysis

1) *FAM time series*: Pitch ( $\rho$ ) is defined as the angle of the x-axis relative to the ground, Roll ( $\phi$ ) is defined as the angle of the y-axis relative to the ground and Theta ( $\theta$ ) 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 angle of the sternum and both thighs was estimated from the accelerometer time series by applying the following arctangent function:

$$AccAngle = \arctan\left(\frac{g_z}{\sqrt{g_x^2 + g_y^2}}\right)$$

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).

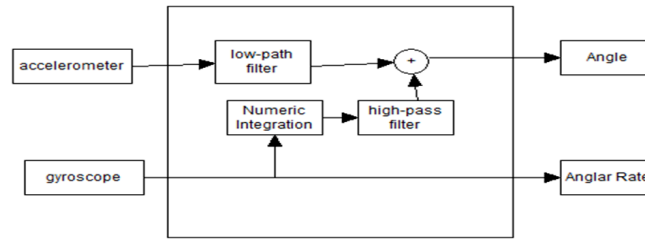


Figure 1. Complementary filter and calibration procedure.

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 Protector (Denali) showed that the difference in mean static angles between the FAM system and the Optrotrak system ranged from minimally  $0.26^\circ$  to maximally  $1.18^\circ$  with a mean difference of  $0.57^\circ$  and SD of  $0.92^\circ$  for five fixed angles ( $0^\circ$ ,  $30^\circ$ ,  $60^\circ$ ,  $90^\circ$  and  $120^\circ$ ). Using a Biodex system (SEMI, Toronto, ON) we imposed amplitudes of  $120^\circ$ ,  $90^\circ$ ,  $60^\circ$ ,  $30^\circ$  and  $5^\circ$  at four different frequencies 80,60, 40, 20 bits/min and found a difference of minimally  $0.06^\circ$  to maximally  $2.3^\circ$  with a mean value of  $0.61^\circ$  and SD of  $0.188^\circ$ . 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  $2^\circ$  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  $-20^\circ$  to  $20^\circ$  and thighs  $25^\circ$  to  $110^\circ$ ), standing (both sternum and thighs  $-20^\circ$  to  $20^\circ$ ); and lying (sternum  $-130^\circ$  to  $-50^\circ$  and thighs  $50^\circ$  to  $130^\circ$ ). If no postures were identified, the posture was labeled "unidentified static activity". 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 is greater than  $20^\circ$ , 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 output of 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.

3) *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. 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).

### **3. 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.

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 ( $p=0.97$ ). A main effect of Velocity was found ( $p<0.001$ ) with no significant interaction effect between tools and walking velocity ( $p=0.99$ ), indicating that both systems accurately captured changes in step frequency.

### **4. Discussion**

The outcomes of the present study indicate that the FAM system not only accurately identify functional activities such as sitting, standing, lying, transfers and walking, 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 both thighs 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 the walking 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. In addition, we are evaluating the reliability and responsiveness of the FAM system in the home and community based setting. We continue 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 that include uni-manual and bi-manual tasks, such as combing and washing hair, washing dishes, throwing balls, etc.

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