A Study on Linear Acceleration of the Wrist During Free-Living

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***Abstract*—Accelerometers have gained popularity in biomedical and m-health applications such as actigraphy or automated dietary monitoring due to their ease of use and their ability to characterize motion. These sensors report raw acceleration from which gravity and linear acceleration must be separated, with commercial packages reporting raw acceleration, linear acceleration or both. New researchers to the field may often be confused when to use raw acceleration or linear acceleration, especially given the susceptibility of linear acceleration to noise, and the lack of published distributions of these signals. This paper provides a short tutorial on obtaining linear acceleration estimates. Using these methods we analyze a large dataset containing 4,680 hours of wrist tracking data, the largest such dataset known to us. We learn the range of wrist motion accelerations, and quantify the expected noise in the linear acceleration signal. We explain the sources of this noise, and a filtering technique to mitigate it. For the first time, we report the range of wrist acceleration values observed during free-living, and quantify the expected range of noise in this wrist acceleration. We show that while previous work has reported average accelerations at the feet and body ranging from 0 - 15g during spots-like activities like walking, running or jumping, wrist acceleration in free-living subjects during daily activities is often much lower, and ranges from 0 - 0.2g. We show that noise in linear acceleration can range from 0 - 0.06g, an overlap of 70%. This suggests that in applications where the wrist acceleration is in this range of noise, linear acceleration may not provide useful features, and researchers should only rely on raw acceleration instead.**

I. Introduction

New applications in m-health are emerging for body-worn sensors in which the linear acceleration signal can provide useful features, such as Parkinsonian tremor detection [1] or automated diet monitoring [2]. Linear acceleration can provide rough estimates of direction and velocity in a motion, however accelerometer signals are known to contain large amounts of noise [3], [4]. This noise is compounded when these sensors are used, as accelerometers do not provide linear acceleration directly. Instead, linear acceleration has to be separated from gravity which is also contained in raw accelerometer output. Previous work has often avoided estimating linear acceleration and instead used raw acceleration for features [5]. Other work has assumed that the effect of gravity can be modeled as a low frequency signal, thus implemented bandpass or high pass filters to separate raw acceleration into gravity and linear acceleration [6]. However, human movement at the wrist is erratic, and will never correspond to a DC or an AC signal [3], and thus, more recently, linear acceleration is estimated from raw acceleration by tracking sensor orientation and subtracting 1g in the direction of earth [1]. This estimate of orientation and linear acceleration is often tracked using proprietary closed source solutions provided by sensor manufacturers, or through open source algorithms such as a complimentary filter [4].

Fig. 1. Photo showing the Shimmer3 wrist mounted platform.

Early work using triaxial accelerometers noted that these devices show low sensitivity to sedentary activities and are unable to register static exercise [3]. It is well known that this calculation is prone to error [7], researchers have assumed the this error is negligible, or not explored further due to missing information in closed-source implementations [8]. Another reason for the lack of information is that the noise in linear acceleration does not affect common applications, such as sports monitoring [9] or step counting [10] where the acceleration being tracked is large.

In this paper, we provide a short tutorial on estimating gravity and linear acceleration from raw accelerometer data. This paper's primary contribution is the quantification of linear acceleration and it's noise from 4,680 hours of wrist activity data collected from 351 subjects over 354 days. This is the largest wrist motion activity dataset ever collected known to us. Data was collected using the wrist watch sized Shimmer3 [11] device shown in figure 1. We show that the range of wrist linear acceleration during free-living is much lower than accelerations reported for other body parts and activities [3], [12], [13]. By learning the range and causes for noise in linear acceleration estimates, we recommend a using a gaussian filter and a mean filter on linear acceleration estimates to mitigate noise while retaining wrist motion signals relative to the subjects body.

II. Methods

In this section we first describe the collection of a wrist activity dataset. We then provide a short tutorial on estimating linear acceleration from raw accelerometer data. We discuss the sources of noise that affect linear acceleration, and a method to estimate linear acceleration noise for visualization. This method is based on the assumption that at periods of rest (zero velocity and zero acceleration), acceleration reported by a system (sensor or algorithm) must be noise. Therefore, noise in linear acceleration can be identified as the values reported by a system during periods of rest. By calculating the statistical variance in samples of angular velocity, periods of rest can be identified as those with low variance in velocity over a small time window. Finally, we describe a mean filter to mitigate this noise, and discuss when linear acceleration is not an appropriate signal for feature selection.

A. Shimmer3 Dataset

The motivation for this work was previous work on an algorithm to detect meals by tracking wrist motion all day [2]. For this work, data was collected using a Shimmer3 [11], a wristwatch sized device housing accelerometer, gyroscope and magnetometer sensors. The Clemson University Institutional Review Board approved this data collection, and subjects provided informed consent. Subjects were asked to wear the device on waking up, and start recording wrist activity data all day, taking the device off only if it risked full immersion in water, such as during swimming or showering. They were instructed to stop recording data when they went to bed at night. The collection resulted in 4,680 hours of wrist motion data from 351 participants. For each participant, the data file contains accelerometer, gyroscope and magnetometer data at 15Hz, along with orientation estimates in the form of quaternions. The sampling rate of 15Hz has been show to be satisfactory for applications such as gesture recognition [14]. The algorithm to detect food intake was developed based on linear acceleration, the estimation of which has been described below.

B. Estimating Linear Acceleration

Microelectromechanical system (MEMS) accelerometers are constructed using spring-like objects that bend in a direction opposite to their motion [15], allowing them to sense the combined effect of acceleration and the gravity vector in their own frame of reference (relativistic acceleration). Previous work often modeled gravity as a low frequency signal, and thus used high pass or band pass filters to isolate linear acceleration [6]. In this work, we obtain linear acceleration a_l from relativistic (raw) acceleration a_r by subtracting the gravity vector in the device frame g_d, as shown in Equation 1.

$$a_l = a_r - g_d \tag{1}$$

This gravity vector g_d can be obtained if the orientation of a device is known. Assuming the orientation is available in the form of a rotation matrix R of order 3×3, the gravity vector in the earth frame g_e = [0 0 1]g can be rotated to the gravity in the device frame g_d:

$$g_d = R\, g_e \tag{2}$$

C. Estimating Orientation (Pose)

When at rest, raw acceleration is equal to the gravity vector, and thus orientation (pose) can be obtained directly. However during motion, gravity needs to be separated from linear acceleration. Another method of tracking orientation is using dead reckoning, where gyroscope data only is integrated over time. However, the noise in gyroscope data causes drifts in these orientation estimates, making them unusable. Today, orientation is often tracked using a family of algorithms commonly known as AHRS (Attitude and Heading Reference Systems). Device manufacturers implement these algorithms in proprietary software such as Apple's Core Motion library [16], or Invensense's MotionProcessor API [17], while some open source sensor fusion implementations also exist [18]. Madgwick et. al recently introduced a complementary filter that fuses magnetic, angular rate and gravity (MARG) to estimate orientation [4]. This algorithm is preferred by researchers due to the availability of open source code implementations programmed in C, C# and Matlab. We hypothesize that proprietary implementations by Apple and Invensense implement variations of this algorithm, modified to work better with factory calibrated settings.

Madgwick's algorithm uses gradient descent to provide orientation estimates in the form of quaternions. While rotation matrices are convenient and easily inferred by humans, quaternions are preferred in software as they are more compact and computationally efficient. Like a complementary filter, the algorithm defines the state of the system by a quaternion $Q = q_0, q_1, q_2, q_3$ that represents the orientation. When new sensor input is available, an estimate of the new orientation Q_a is made using information from the accelerometer and magnetometer data. Another estimate of the orientation Q_ω is made by integrating the gyroscope angular velocity. The orientation at time t, Q_t is then estimated from the quaternion at time t-1, Q_{t-1}, and the estimates Q_a and Q_ω. Full details of this algorithm are provided in [4], while the source code is available at https://x-io.co.uk/open-source-imu-and-ahrs-algorithms/.

The quaternion representing orientation can be converted to a rotation matrix using the equation below:

$$R = \begin{bmatrix} 1-2(q_2^2+q_3^2) & 2(q_1q_2-q_0q_3) & 2(q_0q_2+q_1q_3) \\ 2(q_1q_2+q_0q_3) & 1-2(q_1^2+q_3^2) & 2(q_2q_3-q_0q_1) \\ 2(q_1q_3-q_0q_2) & 2(q_0q_1+q_2q_3) & 1-2(q_1^2+q_2^2) \end{bmatrix}$$

Following this conversion, gravity can be obtained using equation 2, and then linear acceleration can be obtained using equation 1.

D. Noise in Linear Acceleration

We used the previously described method to estimate of linear acceleration from our Shimmer3 dataset. While analyzing this signal we noticed plateaus in the magnitude of linear

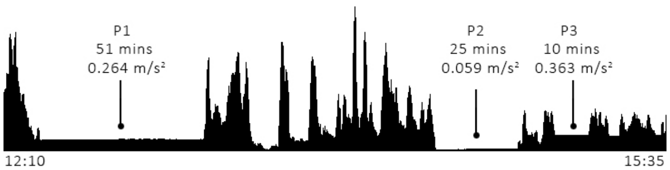

Fig. 2. Magnitude of linear acceleration (Y-axis) vs time (X-axis). Noise can be seen as long plateaus of constant linear acceleration P1, P2 and P3.

acceleration, shown in figure 2. For example, the plateaus seen in figure 2 are of length 10 - 51 minutes, indicating that the visualization of short gestures typical in gesture recognition experiments would not reveal this noise. The range of values (0 to $0.6\,\mathrm{m/s^2}$ (0.06g)), length of time, and flatness of change indicates they are not due to real motion and are instead noise artifacts. These plateaus and indications of noise are not noticable when linear acceleration signals are visualized separately for each axis, or if the duration visualized is short, which is common in applications of accelerometers such as activity or gesture recognition. Given that this noise exists after the raw acceleration has been processed by an AHRS algorithm, it is reasonable to believe that these errors are not corrected by proprietary systems or the Madgwick filter.

E. Sources of Error

Figure 3 shows an overview of the sources of error when calculating linear acceleration. Raw sensors (accelerometers, gyroscopes, and magnetometers) can all be affected by bias due to small offsets in coordinate systems or components during manufacturing [19]. Magnetometer readings can be distorted by local deviations in the magnetic field. Gyroscopes can be used to calculate orientation but the values must be integrated and thus suffer from drift in dead reckoning estimates. An attitude heading reference system (AHRS) algorithm calculates object pose relative to the earth [15]. This pose R is then used to calculate gravity and linear acceleration as shown previously in equation 2.

Errors in pose estimation are unavoidable [15] and even small errors can contribute to significant errors in linear acceleration. The earth gravity vector g_e has a standard value of 1 g = $9.81\,\mathrm{m/s^2}$ but can vary from $9.76\,\mathrm{m/s^2}$ to $9.83\,\mathrm{m/s^2}$ for different locations on earth [20], which can affect the estimation of linear acceleration.

F. Rest Detector

When the device is moving, there is no known method of seperating noise from the true value of acceleration. This is shown in figure 4. Noise can only be separated from acceleration signals when the device is at rest. When the device is not moving, we know linear acceleration a_l should have a true value of 0g. All acceleration sensed can thus be attributed to noise. This is depicted in figure 5.

We used a variance based rest detector to mark datum as rest or motion for visualization. Variance was calculated for both accelerometer and gyroscope signals, thus checking for rest in wrist linear motion and rotation. For each datum

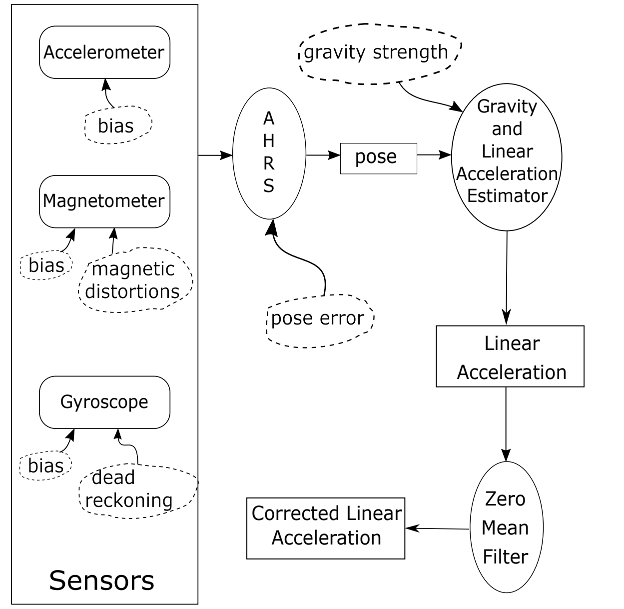

Fig. 3. Flowchart showing the process of estimating linear acceleration, the sources of error contributing to noise, and a filter to obtain corrected linear acceleration.

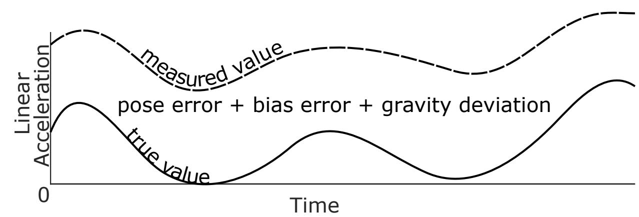

Fig. 4. Graph showing an example of the composition of noise in linear acceleration during motion.

at time index t, the standard deviation σ_t of each axis in the acceleration $\{A_x, A_y, A_z\}$ and gyroscope $\{\omega_\phi, \omega_\psi, \omega_\theta\}$ signals was calculated over a fixed window centered at time index t. The sum of standard deviations of acceleration ($\sigma_{A,t}$ = $\sigma_{x,t} + \sigma_{y,t} + \sigma_{z,t}$) and gyroscope ($\sigma_{\omega,t}$ = $\sigma_{\phi,t} + \sigma_{\theta,t} + \sigma_{\psi,t}$) are then calculated. Time index t is assigned a state $s_t = 0$ (rest) if $\sigma_{A,t} < T_a$, and $\sigma_{\omega,t} < T_\omega$, a state $s_t = 1$ (motion) is assigned otherwise:

$$s(t) = \begin{cases} 0 & \text{if } \sigma_{A,t} < T_A \ and \ \sigma_{\omega,t} < T_\omega \\ 1 & \text{otherwise} \end{cases}$$

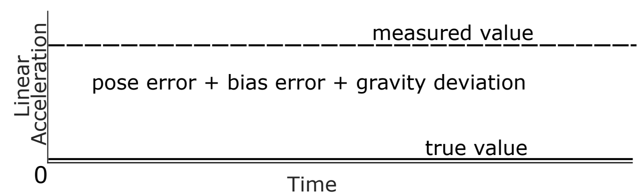

Fig. 5. Graph showing an example of the composition of noise in linear acceleration during rest. As the expected acceleration is 0, any observed value of linear acceleration can be attributed to noise.

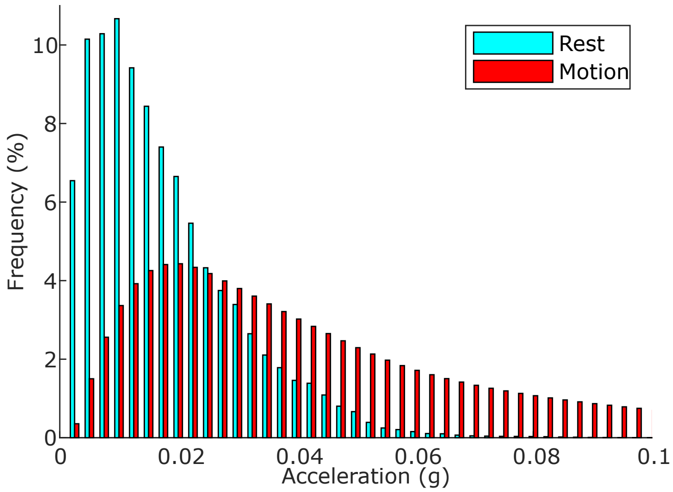

Fig. 6. Linear acceleration values for datum detected as rest (light blue) and motion (dark red). The histogram is long tailed to the right, and has been clipped on the x-axis at 0.1g. The values of linear acceleration at rest can be interpreted as noise. The overlap in the range of noise and signal suggests that a the mean filter should be implemented before this linear acceleration is used for further applications.

The values T_a and T_ω were tuned to 0.008g and 0.04 rad/sec by calculating the maximum value of standard deviation during segments visually identified as rest. The fixed window was tuned to 1 second. This allows the rest detector to detect periods of reasonable wrist rest, while avoiding being triggered by short moments where the sensor is not moving.

G. Zero Mean Filter

Noise in linear acceleration can be mitigated using a zero mean filter (ZMF). For each axis in the linear acceleration signal at each datum $A_{i,t} = \{A_{x,t}, A_{y,t}, A_{z,t}\}$, an average linear acceleration $\bar{A}_{i,t}$ is calculated over a ten second window centered at the datum. This average is then subtracted from the value of linear acceleration to obtain corrected linear acceleration $A'_{i,t}$:

$$A'_{i,t} = A_{i,t} - \bar{A}_{i,t} \tag{3}$$

It is important to note that this zero mean filter practically acts like a high pass filter. While information on the motion of the wrist relative to the body is retained, any information on global movements, like slow motions of the body while walking are filtered out.

III. Results

We analyzed linear accelerations during a free-living day for 351 participants in the Shimmer3 dataset. Figure 6 shows the distribution of acceleration values during rest and motion. We learn that while some instances of high acceleration exist, the distribution of wrist linear acceleration is long tailed to the right. The distribution is concentrated in movements of relatively low acceleration. 50% of the acceleration is <0.01g (figure 6), 90% of the wrist acceleration is <0.04g, and 99.9% of the acceleration is <0.2g.

TABLE I

LINEAR ACCELERATION AT THE WRIST DURING FREE-LIVING IS MUCH LOWER THAN ACCELERATIONS AT OTHER BODY LOCATIONS DURING SPORTS-LIKE ACTIVITIES.

Work	Location	Activity	Acc.
Lundgren et. al [12]	Foot	Jumping	9g - 10g
Lundgren et. al [12]	Foot	Trampoline	10g - 15g
Lucas-Cuevas et. al [13]	Foot	Running	4g - 6g
Cappozzo [21]	Upper Body	Walking	0.8g †
Cappozzo [21]	Lower Back	Walking	0.4g †
Kavanagh et. al [22]	Head	Walking	0.2g †
Rowlands et. al [23]	Wrist	Walking	1.8g †
Rowlands et. al [23]	Wrist	Running	6g †
Rowlands et. al [23]	Wrist	Box Jumping	5g †
Stamatakis et. al [24]	Finger	Finger Tapping	0g - 8g
This Work	**Wrist**	**Free-Living**	**0g - 0.2g**

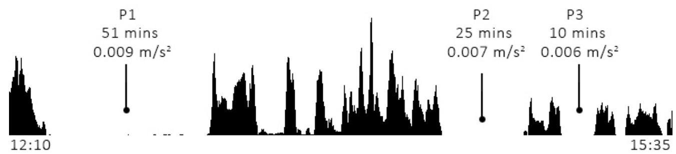

Fig. 7. Magnitude of corrected linear acceleration (Y-axis) vs time (X-axis). Noise is mitigated by the zero mean filter. Plateaus P1, P2 and P3 seen in figure 2 have been reduced to periods of zero linear acceleration.

For the state of rest, linear acceleration values range from 0.00 to 0.06g, which can be interpreted as noise. Figure 6 shows that the average value for noise is in the neighborhood of linear acceleration when the wrist is in motion. More importantly, we learn that 70% of wrist motion lies within the range of noise, explaining why acceleration based features do not perform well in some applications.

When the mean filter is implemented, figure 7 shows that the noise is mitigated during long periods of rest, while the signature of the signal during motion is still retained. Plateaus tend to be minimized to near zero. The magnitude of linear acceleration during periods of time when the object was moving are somewhat reduced but overall trends are still clearly visible.

IV. Discussion

To our knowledge, this is the largest collected dataset that measures the expected range of linear acceleration in human wrist motion during normal daily free-living. Previous work has shown accelerations ranging from 5g - 15g (table I). For example, sports-like activities like jumping or running can produce accelerations in the range of 9g - 15g, finger tapping can produce accelerations in the range of 0g - 6g, while walking and running can produce accelerations in the range of 1.8g - 5g. This is in huge contrast to the linear acceleration at the wrist during free-living, where the range is an order of magnitude lower, between 0g - 0.2g.

This work also quantifies the difficulty imposed by noise sources in linear acceleration calculations. Noise in linear acceleration ranges from 0g to 0.06g, overlapping the range

† Average acceleration value.

of wrist accelerations by 70%. This large interaction between noise and actual linear acceleration is what causes challenges when accelerometers are used in some applications [3]. Consider the application of detecting eating during free-living [2], or detecting free-living activities like writing or using a computer. In these applications, the expected wrist acceleration is well within the range of noise, and thus linear acceleration may not a good candidate for features. We recommend such applications instead rely on features calculated from raw acceleration or gravity, which can indicate orientation. On the other hand, applications such as step counting [10], or Parkinson's tremor detection [24] often analyze acceleration signals of higher amplitude. The noise in linear acceleration (0g - 0.06g) is comparatively low compared to the amplitude in these applications (5g - 15g), and thus does not affect performance.

If linear acceleration is to be used, noise can be mitigated by using the filter described in section II-G. This filter mitigates noise while preserving the general trends that indicate motion. The practical effect of this filter is that local motion (wrist relative to the body) is maintained, while global motion (wrist and body moving over a long period of time, for example walking around a room) is filtered out. A side effect of this method is that global motion is lost (e.g. distance walked by a subject wearing an accelerometer), but local motion is retained (e.g. wrist motion relative to the body).

In conclusion, we recommend researchers using linear acceleration first verify if their application is affected by the noise in linear acceleration. This can be done by visualizing the magnitude of acceleration. If they observe long periods of constant acceleration that is not physically feasible, we recommend they consider using raw acceleration or gravity for features instead. If they do use linear acceleration, a mean filter can be added to mitigate noise and enhance information on the wrist relative to the body, at the cost of losing information on the movement of the entire body itself.

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