Development of a Real-Time Activity Classification and Stability Assessment System for Activity of Daily Living

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Abstract
Accurate, accessible assessments of basic human activities and postures are essential for maintaining quality of life, allowing individuals to preserve physical capabilities that are normally taken for granted. However, existing assessment methods observe subjects only while performing isolated activities within strict experimental controls, a poor model for real-life situations. In this study, a new methodology is proposed to integrate multiple assessment methods with an activity classification algorithm. This algorithm, utilizing data from two accelerometers attached respectively to the sacrum and front side of the thigh, could have future use during consecutive ADLs (activities of daily living) in identifying current activity types and applying corresponding assessment methods to quantify stability levels. The classification structure of this algorithm was developed using a database compiled from thirty subjects performing self-selected normal activities. A pre-recording process was required, which extracted individual thresholds and relative stability assessment standards to accurately classify and assess stability levels. When evaluated, our system performed with over 90% accuracy in activity classification and proved feasible for assessing consecutive ADLs. In the future, the system developed here can be used as an early predictor for instability situations, preserving long-term mobility.

Introduction
Our daily life is composed of various human movements known as activities of daily living (ADLs), which include standing, sitting, and walking. Under standard conditions, these activities can be performed during daily life without conscious thought. However, an individual’s ability to complete ADLs can be jeopardized by environmental, physical, and biological conditions such as a slippery surfaces, uneven floors, or degeneration of movement control due to factors including chronic disease or increased age. This ultimately leads to a decrease in quality of life [1,2]. Under these circumstances, providing real-time stability assessments for real-life situations becomes crucial [3]. Activity classification is a recently developed concept utilizing wearable [4-6] sensing technology to automatically recognize different activities [7,8]. To extract authentic information on ADLs in real-life situations, wearable sensing technologies must be unobtrusive, reliable, and capable of continuous, long-term measuring and recording. One type of biomechanical sensor, the accelerometer, has been used to measure both tilt angles under static conditions and applied acceleration along sensitive axes in dynamic situations; a combination which makes them superior to another current sensor technology [8-11].

Wireless accelerometer systems have also been used to measure postural sway [12,13], gait parameters [14], activity intensity [15,16], and metabolic energy expenditure [17]. Advances in integrated microelectromechanical technology have further improved accelerometers, significantly reducing their size and cost [7,9-11]. Based on these parameters, accelerometers have become the technology of choice for activity classification. The appropriate location of accelerometer attachment is determined by the activities under observation. For instance, sitting and standing positions can be differentiated by accelerometers placed on the dominant thigh [15,18]. In many studies, accelerometer was placed
on the sacrum or waist, close to the center of mass, to classify whole body movements [18-23]. Numerous studies have been able to assess and quantify movement stability during specific activities such as balance control during quiet standing [5], gait performance [2,5], and stair negotiation [6]; however, these studies have little application to real-life situations due to restrictions placed upon them, including experimental protocol, influencing devices, and spatial constraints.

Moreover, ADLs are conducted consecutively in real-life situations, with none of the intervening time seen in experiments when assessment methods are altered between activities. Given these facts, a more practical method is required to assess movement stability during consecutive ADLs without experimental constrains. The stated purpose of this paper is to demonstrate the feasibility of assessing movement stability using multiple integrated methods with a real-time activity classification algorithm. A methodology is proposed that could classify the types of ADLs and alter activity stability assessment methods for the simultaneous assessment of consecutive movements’ stability, as shown in Figure 1. As previous studies have indicated movement control varies between individuals [9], a quantification of relative stability was proposed to measure each individual’s stability levels in given activities through comparison with a self-selected normal activity. This research adopted well-defined windowing techniques, dividing recorded acceleration signals into small time segments termed “sliding windows” [10,16,18,20,24]. In real-time activity classification, the duration between each window refers to the temporal resolution of activity classification. Certain features inside each window were extracted to characterize information, quantifying differences between activities. Following this extraction, activities could be successfully classified by identifying whether or not the extracted features exceed pre-set threshold values [10,19].

![Figure 1: Schematic illustration of proposed methodology.](image)

**Methods**

**Instrumentation**

The TrignoTM Wireless System (Delsys, Boston, U.S.A.), containing multiples wireless accelerometers and EMGworks signal processing package software, was chosen to extract authentic acceleration information in an unconstrained environment. Two accelerometers were attached with adhesive tape to the sacrum and front side of each subject, as illustrated in Figure 2. Each accelerometer measures accelerations in a range of ±1.5g at ±0.001 g/bit (8-bit) resolution with a sampling rate of 148 Hz. Acceleration signals from each accelerometer were transmitted through the wireless network (ISB Band: 2400-2480 MHz) to the system base before undergoing analog transmission from the system base into our proposed system.

![Figure 2: Accelerometer placement and orientation.](image)

**Classification Algorithm**

Signal Calibration: Since the accelerometers produced analog signals in V (voltage) on each axis, signal was used to calibrate voltages into accelerations (g). Assuming that analog signal and acceleration value are linearly related, as shown in Figure 3, their relation can be described by equation (1) and rearranged into equation (2).

\[
V_{(0g)} = V(0g) + Acc \times \frac{V(1g) - V(0g)}{1g - 0g}
\]

\[
Acc = \frac{1g - 0g}{V(1g) - V(0g)} \times \left|V_{(0g)} - V(1g)ight|
\]
Equation (1) and (2) indicate that the calibrated acceleration (g) can be calculated using the recorded voltage value when the vertical axis is aligned with downward gravitational acceleration, perpendicular to the horizontal axis, resulting in respective accelerations of 1g and 0g.

![Figure 3: Linear relation between analog signal and acceleration value.](image)

**Structure of Experiment-Based Classification and Stability Assessment System:** In order to develop a valid, reliable classification algorithm using recorded acceleration signals, our group conducted a pre-experiment involving thirty subjects who performed nine ADLs, including standing, sitting, lying (facing left, right and upward), walking, jogging, and ascending and descending stairs. Acceleration signals were segmented into 0.5s-length windows, with a 0.25s interval between windows (sliding length). An illustration of window and sliding length is shown in Figure 4. According to a previous study [20], static postures (including standing, sitting, and lying down) are distinguishable from dynamic activities (walking, jogging, ascending and descending stairs) using the standard deviation (S.D.) value of resultant acceleration (superposition acceleration from each of the three axes). The static/dynamic threshold of the S.D. was calculated at 0.04g. In application, activities with S.D. values greater than this threshold are considered dynamic, while those with lesser values are considered static. The mean sacral acceleration over sliding windows was used to further classify each static posture. Primarily, static postures were classified into two categories: upright (standing and sitting) and recumbent (facing left, right and upward). Table 1 presents the position features and selected thresholds, based on the previously described pre-experiment. Each threshold was calculated by averaging the midpoints of two postures conducted by the thirty subjects, as shown in Appendix 1-3. When an activity is considered dynamic, additional classification is required. To classify dynamic activities (including walking, jogging, and ascending and descending stairs), each was evaluated as a variation of gait for the purpose of identifying distinct features between activities. First, it was determined that the vertical oscillations caused by jogging are much larger than those from other activities. Therefore, the S.D. value of sacral x-acceleration was chosen as the characteristic feature of jogging see Appendix 4. Second, while descending stairs, the human body experiences a downward movement similar to free falling (zero gravity). Given this, the minimum value of resulting sacral acceleration (superposition of three axes) was the chosen feature or this activity see Appendix 5.

![Figure 4: Window length (0.5s) and sliding length (0.25s) of this study.](image)

**Table 1:** Chosen features and applied thresholds used to classify static postures.

| Static Postures                      | Chosen features               | Applied thresholds            |
|--------------------------------------|-------------------------------|-------------------------------|
| Upright (Standing & sitting) vs.     | Mean value of sacrum X-acceleration | -0.501 g                      |
| Recumbent (Facing left, right & upward) |                               | (Appendix 1)                  |
| Standing vs. sitting                 | Mean value of thigh X-acceleration | -0.642 g                      |
| Face left vs. facing right vs. facing upward | Mean value of sacrum Y-acceleration | -0.441 g, 0.502 g            |
|                                      |                               | (Appendix 3)                  |
Finally, while ascending, the anterior/posterior oscillation is much larger than when walking. Thus, the mean value of sacral Z-acceleration was chosen as the identifying feature for stair ascension see Appendix 6. In order to eliminate outliers created by abnormal activities such as initial and final steps, thresholds were set to encompass 90% of the distribution of each selected activity feature see Appendix 4-6. These thresholds vary with movement control ability and are therefore different between individuals. Accordingly, a pre-recording process for recording self-selected normal activity, as described above, is required for calculating individualized thresholds. Table 2 presents the chosen features and applied individualized thresholds based on pre-experiment. Once classification rules were established for static and dynamic activities, three stability assessment methods were chosen for integration into our system. First, a 95% confidence radius of postural sway was integrated during quiet standing, having been proven a reliable and sensible parameter in past studies [25].

Table 2: Chosen features and applied thresholds to classify dynamic activities.

| Dynamic Activities                        | Chosen features                                  | Applied thresholds                                         |
|------------------------------------------|--------------------------------------------------|------------------------------------------------------------|
| Jogging vs. walking, going upstairs & going downstairs | S.D value of sacrum x-acceleration               | 90% of chosen feature distribution (individualized) (Appendix 4-6) |
| Going downstairs vs. walking & going upstairs | Min value of sacrum resultant acceleration       |                                                            |
| Going upstairs vs. walking               | Mean value of sacrum z-acceleration               |                                                            |

Second, the RMS value of resultant sacral acceleration, widely investigated and discussed in prior research [2], was integrated during walking. Finally, the variance value of anterior/posterior and medial/lateral acceleration, previously applied and proven [6], was integrated during stair negotiation (ascending and descending). In order to quantify the results of the stability assessment, we proposed a normalization calculation (3) to compare values of chosen features in the current activity being tested with recorded values from the analogous self-selected normal activity. These normalized values represent the degree of similarity between current and normal activities, without directional (positive or negative) indication. If the current activity is very similar to the self-selected activity, the normalization value will be close to zero.

\[
\text{Normalization} = \frac{\text{current Activities} - \text{Mean Normal Activities}}{\text{Standard Deviation Normal Activities}}
\]

Selected values for the self-selected normal activities were extracted during the pre-recording process. The structure of our activity classification and stability assessment system, enacted via the user interface of LabVIEWTM 2013 (National Instrument, Texas, U.S.A.) to calculate final results, is illustrated in Figure 5.

Figure 5: Structure of our developed system. \(a_{1x}, a_{1y}, a_{1z}\) and \(a_{2x}, a_{2y}, a_{2z}\) represent the acceleration signals of the sacrum. \(a_{3x}, a_{3y}\) and \(a_{3z}\) represent the acceleration signal of thigh. \(T_J, T_{GD}, T_{GU}\) represent each subject’s individualized thresholds.

The acceleration from both the sacrum and thigh were segmented into windows for further evaluation with this process. Before each trial, a pre-recording process was performed to record chosen feature values from the individual’s self-selected normal activities. The system then automatically extracted individualized thresholds and relative stability assessment standards from this data, as shown in Table 3. The overall procedure of the developed system is illustrated in Figure 6. First, two accelerometers were calibrated by aligning axes in the downward and horizontal directions. Second, self-selected normal activities (including standing, walking, jogging, and ascending and descending stairs) were pre-recorded, and individualized thresholds and relative stability assessment standards were calculated from extracted records. These values were used to normalize stability assessment results. Finally, we conducted real-time classification, comparing each activity’s chosen feature with pre-determined (for static postures) and individualized (for dynamics activities) thresholds. Stability assessments were performed by normalizing current stability levels, comparing current values to their relative stability standards based on classified activity types.

Table 3: The individualized thresholds and relative stability assessment standards extracted from the pre-recording process.

| Activity            | Individualized Thresholds | Relative Stability Assessment Standard       |
|---------------------|---------------------------|----------------------------------------------|
| Standing            | None                      | 95% Confidence Radius                        |
| Walking             | Mean Value of Z-acc.      | RMS Value of Resultant Acc.                  |
| Jogging             | S.D. value of X-acc.      | None                                         |
| Going Upstairs      | Mean Value of Z-acc.      | Variance Value of Y, Z-acc.                  |
| Going Downstairs    | Minimum Value of Resultant acc. | Variance Value of Y, Z-acc. |

Figure 6: Procedure of the developed system.

Results

Experimental Setup

Five healthy, young and male subjects (height: 1.69 ± 0.39 m, weight: 67.8 ± 6.4 kg, age: 23.2 ± 1.5 years) were recruited to participate in a systematic evaluation to determine the accuracy of the developed activity classification algorithm and performance of the stability assessment system. All subjects were in good health, with no history of neural or musculoskeletal diseases. Informed consent, proved by the Institutional Review Board of Taipei Veteran General Hospital, was given before the experiment. Following calibration, two accelerometers were attached to each subject: one over the sacrum and the other on the front side of the dominant thigh. Next, the pre-recording process was completed, during which each subject performed self-selected normal activities including standing, walking, jogging, and ascending and descending stairs. The developed system automatically extracted their individualized thresholds and relative stability assessment standards from the recorded data, allowing further classification and assessment of ADLs. Each subject was then instructed to perform a series of ADLs, described below, twice.

a) ADLs series:

Standing → Sitting → Recumbent (Facing upward) → Recumbent (Facing left) → Recumbent (Facing right) → Walking → Going Upstairs → Standing → Going Downstairs → Walking → Jogging → Standing

In the first run-through, the five subjects performed the ADL series without constraints. During the second run-through, several types of environmental disturbances were introduced, as listed in Table 4. Subjects were instructed to perform each activity for at least five seconds.
Table 4: List of environmental disturbances used in the system evaluation.

| Standing                          | Upward Reaching |
|----------------------------------|-----------------|
| Forward Reaching                 |                 |
| Walking                          | Heavy Carriage on Dominant Hand |
|                                 | Walking on a Cushion |
|                                 | Obstacle crossing |
|                                 | Walking on Slippery Surface |
| Stair Negotiation                | Going Upstairs with Heavy Carriage |
|                                 | Going Downstairs with Heavy Carriage |

Data Analysis

To quantify the classification accuracy provided by the developed system, the concepts of sensitivity (true positive rate) and specificity (true negative rate) were introduced. Figure 7 presents a sample confusion matrix of actual activities and classified results for a hypothetical comparison test in which only three types of ADLs would be performed and classified. Activity A can be used as an example: sensitivity is defined as the probability that the developed system identifies activity A correctly during performance. Specificity is defined as the probability that the developed system identified non-A (activity B or C), given that the subject were actually performing non-A (activity B or C). Equations for sensitivity and specificity are listed in (4) and (5).

\[
\text{Sensitivity} = \frac{I}{I + (II + III)} \\
\text{Specificity} = \frac{(IV + VI + VIII + IX)}{(IV + I + FI + VII + FII + IX)}
\]

Figure 7: Confusion matrix of actual activity and classified results.

Experimental Results

Classification Accuracy: The classification accuracies, provided by our system during activity performance without environmental disturbances, are presented in Table 5. The developed system provided over 95% sensitivity with nearly 100% specificity for static postures, and approximately 90% sensitivity with greater than 95% specificity during dynamic activities.

Table 5: Sensitivity and specificity of each activity during system evaluation.

| Activity                  | Sensitivity | Specificity |
|---------------------------|-------------|-------------|
| Standing                  | 96.64%      | 99.71%      |
| Be Seated                 | 96.62%      | 99.93%      |
| Lying (Facing Upward)     | 98.73%      | 100.00%     |
| Lying (Facing Left)       | 98.53%      | 100.00%     |
| Lying (Facing Right)      | 97.69%      | 99.89%      |
| Walking                   | 91.92%      | 98.00%      |
| Jogging                   | 91.16%      | 100.00%     |
| Going Upstairs with HC    | 89.74%      | 95.66%      |
| Going Downstairs with HC  | 91.49%      | 99.58%      |

Relative Stability Results with Environmental Disturbances:

In this study, normalized results represent how similar the current activity and self-selected normal activity were, as calculated by equation (3). Normalized values closer to zero indicate greater similarities between self-selected normal and current activities. Figure 8 presents the normalized results during disturbed activities. For disturbed standing, larger normalized values were observed during both upward and forward reaching. Larger normalized values were also seen during disturbed walking with heavy carriage on the dominant hand, walking over a cushion, and crossing an obstacle; however, walking on slippery surface resulted in much lower normalized values. For disturbed stair negotiation, both ascending and descending stairs with heavy carriage presented similar normalized values to walking on a slippery surface, notably smaller than other disturbances.

Discussion

Table 5 presents the sensitivity and specificity evaluated in our developed system. Each axis measured only the gravitational acceleration, allowing calculation of the orientation angle with respect to the gravitational acceleration (downward) by simply averaging acceleration signals within each window (0.5 second). Accelerometers measured no significant movements when subjects performed static postures, and as a result, no significant variations or oscillations are seen in each window. Classification accuracy for static postures was quite excellent. Both sensitivity and specificity of static postures were above 95%. In reality there are variations...
between each subject when performing these static activities due to factors such as stoop and limb length; however, Appendix 1-3 show that such variations were insignificant and tolerable, allowing the use of pre-determined thresholds for classification. As for dynamic activities, the variation between values of consecutive windows was too great for the definition or application of pre-determined thresholds even though Appendix 4-6 indicate the chosen features successfully quantify differences between activities.

In the pre-experiment, each subject performed dynamic activities with their own pattern, resulting in a wide variation of S.D. values. For example, the largest S.D. value for subject 04 in Appendix 4 during normal jogging is approximately 0.75g, yet for subject 22 the largest S.D. value exceeds 1.6g. Thus, the extraction of individualized thresholds was considered essential and necessary. This conclusion was supported by previous studies, which have indicated that movement control ability varies between individuals [9], implying that using fixed stability standards to assess dynamic activities in different individuals is inappropriate and impractical. A pre-recording process, measuring self-selected normal activity and quantifying individualized thresholds, is crucial for this system. Figure 8 presents the results of our stability assessment with environmental disturbances. In order to maintain balance during standing, subjects’ bodies swayed in both the medial/lateral and anterior/posterior directions. The observation of postural sway was considered to quantify balance control with and without environmental disturbances. Previous results have indicated that balance control ability would decrease during forward and upward reaching.

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Figure 8: Normalized results assessed by developed system during disturbed activities.

Normalized results were consistent with expectations, showing that forward reaching, which pushes the center of mass (COM) toward the boundary of the base of support (BOS), caused larger postural sway than upward reaching. During walking, normalized results were greater than 0 during all disturbances except for walking over a slippery surface. This finding coincided with previous studies, which have indicated that subjects tend to apply conservative strategies including shortening step length and lowering impact force and angle during heel strike to avoid of slip-and-falls incidents [26]. This study explored the possibility and feasibility of applying existing assessment methods to consecutive ADLs by automatically switching assessment methods based on the classification results. To determine the efficacy of this methodology, proposed in Figure 1, it was essential to investigate system performance through observation of the normalized relative stability values during consecutive ADLs. The upper part of Figure 9 presents these normalized results as assessed by single method during consecutive activities. For a more comprehensive description of this strategy, observe the 95% confidence radius of postural sway during performance of undisturbed activities.

When the subject performed static upright standing, the normalized value was close to zero as expected. However, following standing, the subject performed dynamic activities including walking (W) and ascending (U) and descending (D) stairs. During these, recorded normalized values rocketed to approximately 100. This indicated current activity levels a hundred times higher than static standing. Initially, this seems illogical, as subjects were still performing normal activities during walking and stair negotiation. This phenomenon can be attributed to a mismatch between the activity being performed and the stability assessment method being applied. Our activity classification system was built to eliminate this mismatch by identifying types of activity and alternating assessment methods automatically. The lower part of Figure 9 presents the normalized value as calculated by switching assessment methods during consecutive activities. Obviously, the classification system was able to correctly identify types of ADL while subjects performed each activity without disturbance, and correctly applied the corresponding assessment methods.

The normalized value was kept between ±5 and oscillated around 0, implying normal activities were being performed.
Therefore, by comparing two graphs in Figure 9, it can be seen that integrating an automatic activity classification system with multiple stability assessment methods is feasible and valid. In the lower part of Figure 9, fluctuations in normalized value were observed during transitions between activities. This may suggest that the risk of falling or loss of balance is higher during the transition phase than in a continuous activity. This finding coincides with definition of “initial gait” found in previous studies, which is distinct from a stable gait [27]. Unfortunately, it is impossible to continue performing one ADL while simultaneously performing or transferring to another; and as such, these destabilizing transition phases are unavoidable.

Figure 9: Comparison of assessment methods for consecutive ADLs with and without an activity classification system using subject 01 as an example. S: Standing; W: Walking; U: Going upstairs; D: Going downstairs.

Conclusion

In this article, we presented a new methodology for assessing activity stability levels during ADLs and consecutive activities in real-time, based on the data of two triaxial accelerometers. The novel classification algorithm requires a pre-recording of subjects performing self-selected normal activities to extract individualized thresholds and stability assessment standards. During real-time evaluation, the developed system provided over 90% accuracy and successfully quantified subjects’ level of stability during environmental disturbances. Moreover, our system proved effective during consecutive ADLs and suitable for utilization in real-life situations. We propose for consideration in future investigations the improvement of hardware, optimizing transmissions and processes, and functional integration, involving such aspects as energy expenditure or long-term monitoring.

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