# Automatic Individual Calibration in Fall Detection – An Integrative Ambulatory Measurement Framework

**Jian Liu** and
Health and Human Performance, University of Houston, Houston, TX, USA, 104 GAR, 3855 Holman St., Houston, TX 77204-6015, jliu30@uh.edu

**Thurmon E. Lockhart**
Industrial and Systems Engineering, Virginia Tech, Blacksburg, VA, USA

## Abstract

The objective of the current study was to demonstrate the utility of a new integrative ambulatory measurement (IAM) framework by developing and evaluating an individual calibration function in fall detection application. Ten healthy elderly were involved in a laboratory study and tested in a protocol composed of various types of activities of daily living (ADLs) and slip-induced backward falls. Inertial measurement units attached to the trunk and thigh segments were used to measure trunk angular kinematics and thigh accelerations. The effect of individual calibration was evaluated with previously developed fall detection algorithm. The results indicated that with individual calibration, the fall detection performance achieved approximately same level of sensitivity (100% vs. 100%) and specificity (95.25% vs. 95.65%), however, response time was significantly lower than without (249ms vs. 255ms). It was concluded that the automatic individual calibration using the IAM framework improves the performance of fall detection, which has a greater implication in preventing/minimizing injuries associated with fall accidents.

### Keywords

Ambulatory measurement; fall detection; fall intervention; slips and falls

## Introduction

Ambulatory measurement (via accelerometers, gyroscopes, etc.) is gaining vast popularity in biomechanical research. Compared to the conventional motion capture systems (e.g., optical-, magnetic-, and sonic-based systems), ambulatory sensors have the general advantages of being portable, lightweight, and cost effective (see review, Aminian and Najafi, 2004). Without being confined to a dedicated measurement space, they are extremely suitable for long-term monitoring in a daily living environment. Over the years, ambulatory measurement technology has been successfully utilized in gait analysis (Aminian et al., 2004; Mansfield and Lyons, 2003; Zijlstra and Hof, 2003; Sabatini et al., 2005), classification of activities of daily living (ADLs) (Lyons et al., 2005; Mathie et al., 2004; Najafi et al., 2003; Nyan et al., 2006), physical activity assessment (Zhang et al., 2003; Chen and Bassett, 2005), fall risk assessment (Najafi et al., 2001; Giansanti, 2006; Lockhart and Liu, 2008), and general biomechanical research (Luinge et al., 2007; Simcox et al., 2005). Ambulatory sensors are also fundamental for developing fall event detection technology (see recent review, Noury et al., 2008).

The specific methods in ambulatory measurement studies can be categorized in different manners. From the perspective of processing time, different approaches can be generally categorized into either non-real-time processing or real-time processing. Non-real-time

processing is most commonly adopted in ambulatory measurement (Najafi et al., 2003; Lyons et al., 2005; Mathie et al., 2004). For this type of approach, data collection is separate from data processing. The measurements from the ambulatory sensors can be either stored in the on-board storage device for later retrieval or transmitted to a local computer. The on-board sensing device may include some preliminary data processing capabilities such as filtering, amplification, and A/D conversion (Karantonis et al., 2006). The core function of signal feature extraction and classification, however, are performed after all the data is available. For the real-time approaches, data analysis is performed simultaneously with data capturing, with or without time delay. Compared to the non-real-time approaches, real-time analysis is much less frequently used due to the constraints on processing time.

Both real-time and non-real-time approaches have their unique advantages. The main advantage of non-real-time approaches is that there is virtually no limitation on the time available to perform the data analysis. Consequently, there are no constraints on how complex and time-consuming the analytical algorithms can be. More importantly, as indicated by Karantonis et al. (2006), the current motion can be determined using the information regarding past and future events. Nevertheless, real-time analysis does have one unparallel advantage that it is the only choice for time-critical applications such as fall event detection. To the authors' knowledge, currently there is no ambulatory measurement study attempting to incorporate both the non-real-time and real-time processing together, which may show great potentials in many different applications including fall event detection.

Existing fall detection research (see review, Noury et al., 2008) is suffering from the dilemma between false alarms and misdetections, which partly results from heterogeneity of between-subject motion characteristics (Sekine et al., 2000). In a fall detection algorithm, a generic threshold determined from the group motion characteristics can hardly achieve optimal performance at an individual level. One way to improve the detection performance is to adopt an individualized threshold. Though seemly attractive, the traditional way to conduct individual calibration is facing practical constraints because it is a supervised process and requires a dedicated facility and personnel (Sekine et al., 2000). A way to perform individual calibration automatically without human intervention would theoretically improve the performance of fall detection, which is a valuable fall intervention strategy as it not only prevents/minimizes delayed medical attention for fall victims (Noury et al., 2008) but also paves the way for developing a wearable fall protection system (e.g., airbag technology (Fukaya and Uchida, 2008).

Therefore, the objective of this study was to demonstrate the utility of a new integrative ambulatory measurement (IAM) framework by developing and evaluating an individual calibration function in fall detection application. The IAM framework integrates both real-time and non-real-time processing capabilities. It was hypothesized that the fall detection performance would be significantly improved with the IAM framework than without, as quantified by higher sensitivity, higher specificity, and lower response time.

## Methods

### Concept of IAM framework

The concept of the IAM framework is to integrate both real-time and non-real-time processing capabilities together, to split the functions of the target application, and to allocate individual functions to the most appropriate processing module. It is expected that such a framework will maximize the efficacy of each individual processing module and optimize the overall performance of the target application.

In terms of human ADL classification, most of the applications are not time critical and are suitable to be processed in a non-real-time manner. For applications like fall event detection, especially the prior-to-impact type design (Nyan et al., 2006), rapid response is of one of the top priorities, which dictates that fall accidents can only be detected in a real-time manner.

In addition to simply putting two processing modules together, the IAM framework also emphasizes the importance of being able to share information between the real-time and the non-real-time modules. The real-time module is responsible for capturing and storing the data to be further processed by the non-real-time module. Meanwhile, the non-real-time module should be able to provide feedback to update some critical parameters in the real-time module so as to improve the real-time processing performance.

Taking fall event detection scenario as an example, the core component of this application, fall detection, is allocated to the real-time processing module, while the individual calibration and ADL classification functions are allocated to the non-real-time processing module. A schematic illustration of the IAM framework in this particular case is shown in Figure 1. Specifically, the real-time module of the IAM framework is responsible for fall detection and data storage during up-time, which is the period when the fall detector is functioning (e.g., day-time). A new fall detection algorithm (Liu and Lockhart, under review) is implemented in this module. Simultaneously, the real-time module also controls the data storage unit, which saves the obtained data into on-board memory without processing. These stored data is transferred and processed in the non-real-time module during nap-time which is the period when the fall detection is not required (e.g., night-time or scheduled maintenance period).

It should be emphasized that the fall event application is just a specific scenario, which the IAM framework may be well suitable for. This framework by itself dictates neither the choice of analytical algorithms nor the hardware configurations (e.g. types of ambulatory sensors, communication protocols, computing platforms, etc). With such flexibility, the IAM framework is expected to be able to accommodate different application scenarios.

## Concept of individual calibration

The individual calibration function is designed to complement the fall detection process by updating the fall detection thresholds automatically. This function operates in the non-real-time module within the IAM framework.

One important way to improve the fall detection performance is to employ an individualized detection threshold. To obtain such individual-specific information automatically, regular ADLs have to be recognized. This function is allocated to the non-real-time module. While the real-time module is continuously active, the non-real-time module only operates discretely during certain time slots (i.e. nap-time). It is expected that there will be certain periods of nap-time for the real-time component to pause. In the fall event detection case, this nap-time could be at night when the users take off the device or a specifically assigned weekly or even monthly maintenance period. During the nap-time, the data measured during the up-time is retrieved and analyzed. An ADL classification algorithm is implemented to extract the motion feature relevant to each identified motion. An individual calibration algorithm is implemented to obtain an individual-specific fall detection threshold.

Conceptually, the individual calibration is based on the relationship between fall detection threshold (TH) and two of the detection performance measures: sensitivity and specificity. TH is a unitless quantity and is used in the fall detection equation to determine whether a fall has or has not occurred. For any threshold-based detection algorithm, the detection performance is dependent on the choice of a specific TH. With the changing TH, the

sensitivity and specificity will move in opposite directions (Zweig and Campbell, 1993). As one increases, the other will decrease. Ideally, there might be cases when a fall detection algorithm is so effective that a single or a range of TH can achieve maximum (100%) sensitivity and specificity simultaneously. In reality, however, sensitivity and specificity rarely reach their maximum simultaneously and an increase in TH will normally result in an increase in sensitivity but a decrease in specificity. Consequently, a compromise in performance measures has to be made in choosing a single or a range of TH for the algorithm. A generic or optimal TH for a specific algorithm is usually determined in a way that the algorithm can reach desirable levels of sensitivity and specificity for a group of users. In terms of each individual user, however, an individualized TH instead of a generic TH may achieve a better combination of sensitivity and specificity.

In practice, the individual calibration works in a way that it gradually adapts the generic TH to a more individualized TH based on the user-specific motion characteristics during ADLs. Suppose an ADL monitor constantly records and classifies an individual's daily behaviour over a period of time. Such a user-specific ADL dataset is sufficient to compute one of the fall detection performance measures: specificity. A user-specific TH can then be determined at a desirable level of specificity. Suppose an ADL monitor is worn for a prolonged time, a large ADL motion characteristic dataset will be available to compute a reliable and accurate TH which is individualized for that particular user. With this adapted TH, it is possible to achieve an optimal combination of sensitivity and specificity at an individual level.

Specific to the current study, an analytical scheme (Figure 2) was implemented. The trunk angular kinematics was analyzed. The fall detection algorithm adopted in the current study has been documented in detail in another publication (Liu and Lockhart, under review) and only requires trunk sagittal angular angle ($\alpha$) and angular velocity ($\omega$) measurements. Previous study has demonstrated that slip-induced fall accidents has a distinctive trunk angular kinematics pattern (Liu and Lockhart, 2009).

For any particular individual, the trunk angular kinematics ($\alpha$ and $\omega$) were gathered for each repetition of the same motion. Predictive values were obtained by processing these measurements using the fall discriminant function. An activity ROC curve (Liu and Lockhart, under review) was constructed for this individual using all the ADL trials. The minimum TH that could achieve a desirable level of specificity, which was 95% in the current study, was determined as the individualized TH for this individual. In case that 95% specificity was not possible, the TH corresponding to the highest specificity was used.

### Experimental Evaluation

**Participants—**Ten elderly participants (age = 75±6 years, weight = 74.1±9.1 kg, height = 174±7.5 cm) were recruited for this study. They were deemed to be in good physical health by the study physician. Prior to data collection, a sample size calculation has been performed based on the results from a pilot test and concluded that a sample size of 10 is sufficient to achieve a statistical power of 0.84 with the Type I error less than 0.05. Informed consent was approved by the IRB at Virginia Tech and obtained from each participant.

**Apparatus and Procedures—**The detailed experimental protocol has been documented elsewhere (Liu and Lockhart, 2009). Briefly, each participant was instructed to perform a series of ADLs composed of various types of sitting down and standing up, lying down, and, bending over to pick an object from the ground. Unexpected slip-induced backward falls were induced by having the participants walk over a slippery surface (Liu, 2009; Liu and Lockhart, 2009). Optical motion analysis system (ProRefelx, Qualysis, Sweden) was used to establish a reference measurement for the ADL classification. One inertial measurement unit (Inertia-Link, MicroStrain, USA) attached to the trunk segment (close to sternum) was used

to capture trunk angular kinematics (α and ω) for the purpose of fall detection. In addition, one tri-axial accelerometer (WiTilt v2, SparkFun, USA) attached to one of the thigh segment was used to facilitate the ADL classification.

**Data analysis**—Detailed signal processing can be found elsewhere (Liu and Lockhart, 2009). For the purpose of ADL classification, the motion analysis data was used as a reference measurement. Segmentation of the captured motion trial into static phases and dynamic phases, and documentation of the nature of the posture/activity was performed subjectively by the experimenter. The time resolution of this activity log was expected to be about 0.1s. The algorithm for automatic classification of ADLs was adapted from a published orientation-based algorithm (Lyons et al., 2005). The computer-generated activity log was then compared with the activity log generated manually from the motion analysis system for each participant.

For the purpose of individual calibration, a fall discriminant function (Equation 1, Liu and Lockhart, under review) was first applied to all the ADL trials for a given individual to obtain resultant predictive values. The search for an individualized TH started from the minimum predictive value and stopped until the specificity for that individual dropped below 95%. In other words, the minimum predictive value associated with 95% specificity was regarded as the temporary TH for that individual. The higher value between temporary TH and the generic TH was then taken as the individualized TH.

$$F_{\text{Algorithm}} = -0.5251 + \begin{pmatrix} \alpha \\ \omega \end{pmatrix} \cdot \begin{pmatrix} -0.0586 \\ -0.0070 \end{pmatrix} + \begin{pmatrix} \alpha \\ \omega \end{pmatrix} \cdot \begin{pmatrix} 0.0246 & -0.0010 \\ -0.0010 & -0.0004 \end{pmatrix} \cdot \begin{pmatrix} \alpha \\ \omega \end{pmatrix}^{-1} \quad \text{Equation 1}$$

where α and ω indicate trunk sagittal angle and trunk sagittal angular velocity, respectively, with flexion being positive. A particular trial will be detected as fall if $F_{Algorithm}$ of any joint instantaneous values (α and ω) of this trial is less than a predetermined detection threshold (TH).

Three previously defined performance measures (response time, sensitivity and specificity) were calculated to quantify the fall detection performance with and without individual calibration. Response time measures the time taken for a fall to be detected after it is initiated, with lower response time indicating better performance. Sensitivity measures the percentage of correctly detected falls while specificity measures the percentage of correctly detected ADLs.

As a proof of concept study, all of the data processing was performed offline in a local computer using a custom-designed program in MATLAB (2007a, MathWorks, USA).

**Statistical analysis**—A one-way within-subject ANOVA was performed in SAS 9.1 (SAS Institute, USA) with individual calibration (with and without) as the independent variable and response time as the dependent variable. The algorithms without and with the individual calibration were denoted as algorithm A and B, respectively. A significant level of p   0.05 was adopted.

## Results

Totally 179 ADL and 11 backward fall trials were analyzed in this study. The influence of TH on sensitivity and specificity is illustrated in Figure 3. In general, increases in sensitivity resulted in decreases in specificity, or vice versa. As a compromise between sensitivity and specificity, the generic TH was determined to be −4.994 based on the entire dataset for the

current study. The sensitivity and specificity associated with the generic TH were found to be 100% and 95.65%, respectively.

After individual calibration, the THs for four out of ten participants were able to be enhanced (Table 1). For each individual, another fall detection algorithm configuration (B) was constructed with original algorithm (A) and individualized TH. In other words, for four out of ten participants, algorithm B was different from algorithm A. The overall sensitivity and specificity of algorithm B were found to be 100% and 95.27%. Compared to algorithm A, the algorithm B achieved the same level of sensitivity (100%) and an approximately same level of specificity (95.25% vs. 95.65%).

The ANOVA test indicated that individual calibration had a significant effect on response time (p = 0.0002). The response time was found to be significantly lower by algorithm B (249±24 ms) than by algorithm A (255±22 ms). In other words, individual calibration significantly enhanced fall detection performance by reducing the response time.

## Discussions

The objective of this study was to propose a new IAM framework that can take advantage of both non-real-time and real-time processing. To demonstrate the utility of the IAM framework in fall detection application, an individual calibration function was developed and evaluated with ADLs and slip-induced backward falls.

The findings from the current study demonstrated the feasibility of IAM framework to carry out individual calibration automatically, without an explicit and supervised calibration process during the data measurement. Individualized THs, however, were not able to be obtained from all the participants (Table 1). This was expected because first, the generic TH can be conceptually considered as a 'balanced' choice among a group of individualized THs. Therefore, an individual's TH may be higher or lower than the generic TH. Second, the current individual calibration algorithm was designed in such a way that it would only return an individualized TH that was higher than the generic TH. The rationale behind this logic is that the detection performance when an algorithm adopts a TH higher than the generic TH is predictable. For that individual, the sensitivity of the algorithm will at least remain the same, if not increase, while the specificity remains the same. On the contrary, the detection performance is unpredictable when an algorithm adopts a TH lower than the generic TH. For that individual, even though the specificity associated with the lower TH may increase, the corresponding sensitivity may decrease to a level that would render the entire fall detection algorithm useless in detecting fall events for that individual. Therefore, individualized THs would not be lower than the generic TH for all the participants.

Despite the feasibility to compute and adopt individualized TH, the effect of the individual calibration on the fall detection performances was not substantial in the current study. Both sensitivity and specificity were found to remain approximately the same for algorithms with and without individualized TH. Even though the response time from the algorithm with individualized TH was statistically lower than that from the algorithm without, the reduction in response time was found to be only 2.4% or 6ms in average. Previous study (Sekine et al., 2000) classified walking patterns using individual-specific thresholds and considered individual-specific thresholds critical in their pattern classification algorithm. To the author's knowledge, however, current study is the first effort which quantitatively measures the effect of individual calibration.

The seemingly small benefits offered by the individual calibration may be explained from three aspects. First, it may be due to the so-called ceiling effect. In the current study, the sensitivity of the algorithm without the individualized TH already reached maximum

(100%). This left no room for further performance improvement in the current study. Second, it may be due to the fact that the actual detectable falling activity was an extremely rapid process. Even though for some participants, it appeared that the individualized TH was dramatically reduced comparing to the generic TH, the reduction in response time was not obvious. Third, due to the extensive screening criteria, the participants in the current study represented a more homogenous population than the general elderly. It is anticipated that the effect of the individual calibration on fall detection would be greater for a more diverse user group in reality.

As a proof of concept research, the current study is associated with a number of limitations and simplifications. First of all, successful and accurate individual calibration is highly dependent on the accurate classification of common ADLs and more advanced ADL classification schemes than the one adopted in the current study are available (for example, wavelet technique (Najafi et al., 2003)). Nevertheless, the proposed IAM framework neither dictates nor restricts the choice of ADL classification algorithm. An arbitrary complex and resource-consuming ADL algorithm can be easily incorporated in the future studies.

Second, the selection of individual threshold based on 95% specificity is experimental in the current study. The rationale is that individual threshold has to be selected in a way to balance between sensitivity and specificity, thereby to achieve a compromise between effectiveness of the technology (i.e., being able to detect a fall when it happens) and user compliance (i.e., without substantial false alarms). Future studies to quantify or model the relative costs (and a prior probabilities) of misdetections and false alarms would help establish a more objective basis for selecting individual threshold.

Third, though the IAM framework differentiate real-time and non-real-time processing, all the data analyses (e.g., individual calibration, fall detection, etc.) were offline processed in a local computer in the current study. The next step would be to construct a prototype system with data buffering and on-line processing capability, and to evaluate its performance in a semi-naturalistic living environment (Bao, 2003).

Additionally, current study is also limited in sample size and diversity of participant population. Future studies involving larger sample size and diverse participant population (e.g., patients with movement disorders) would not only enhance the external validity of the proposed method but also help demonstrate the advantage of adopting individual calibration.

In summary, the current study proposed a new IAM framework incorporating both real-time and non-real-time processing modules, and applied this framework in fall event detection scenario by enabling the individual calibration automatically. It was concluded that individual calibration can significantly improve the performance of fall detection, which could ultimately help prevent/minimize the injuries associated with fall accidents.

## Acknowledgments

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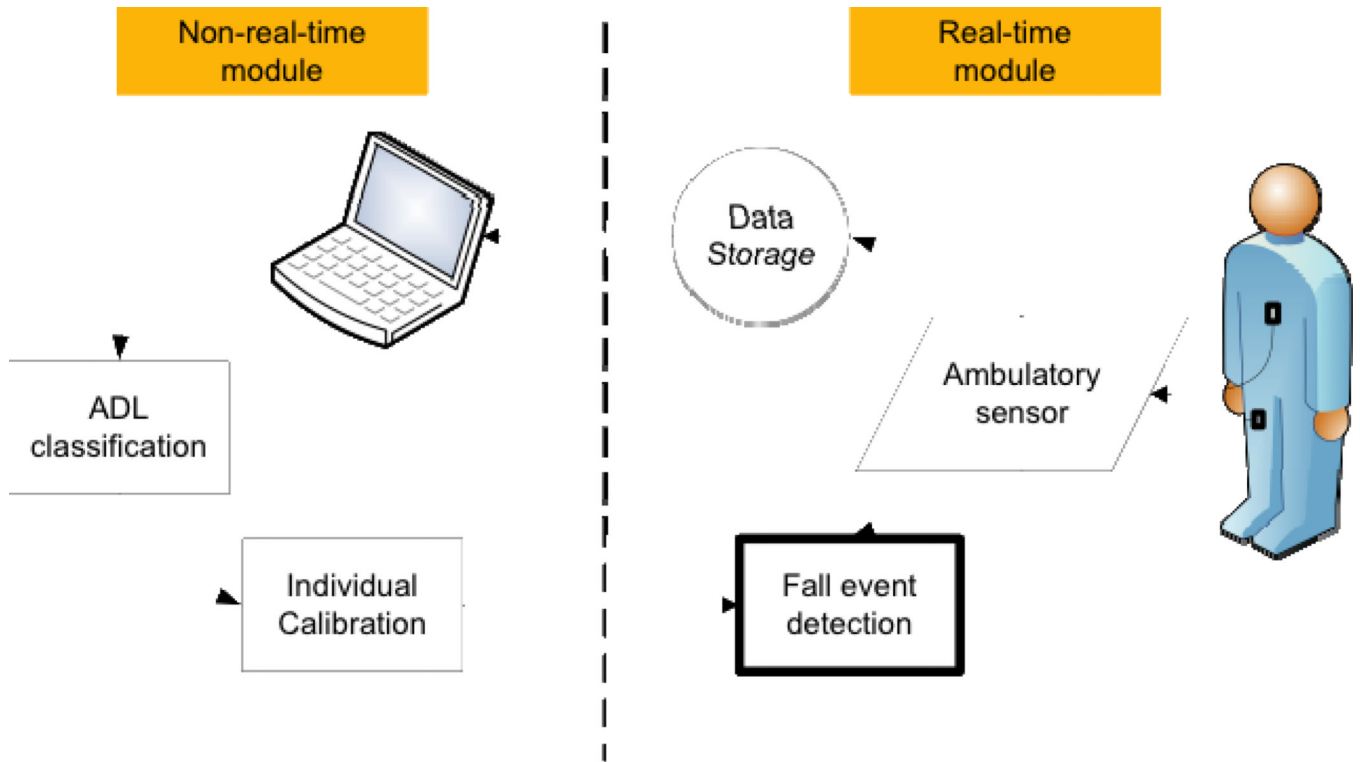
**Figure 1.**
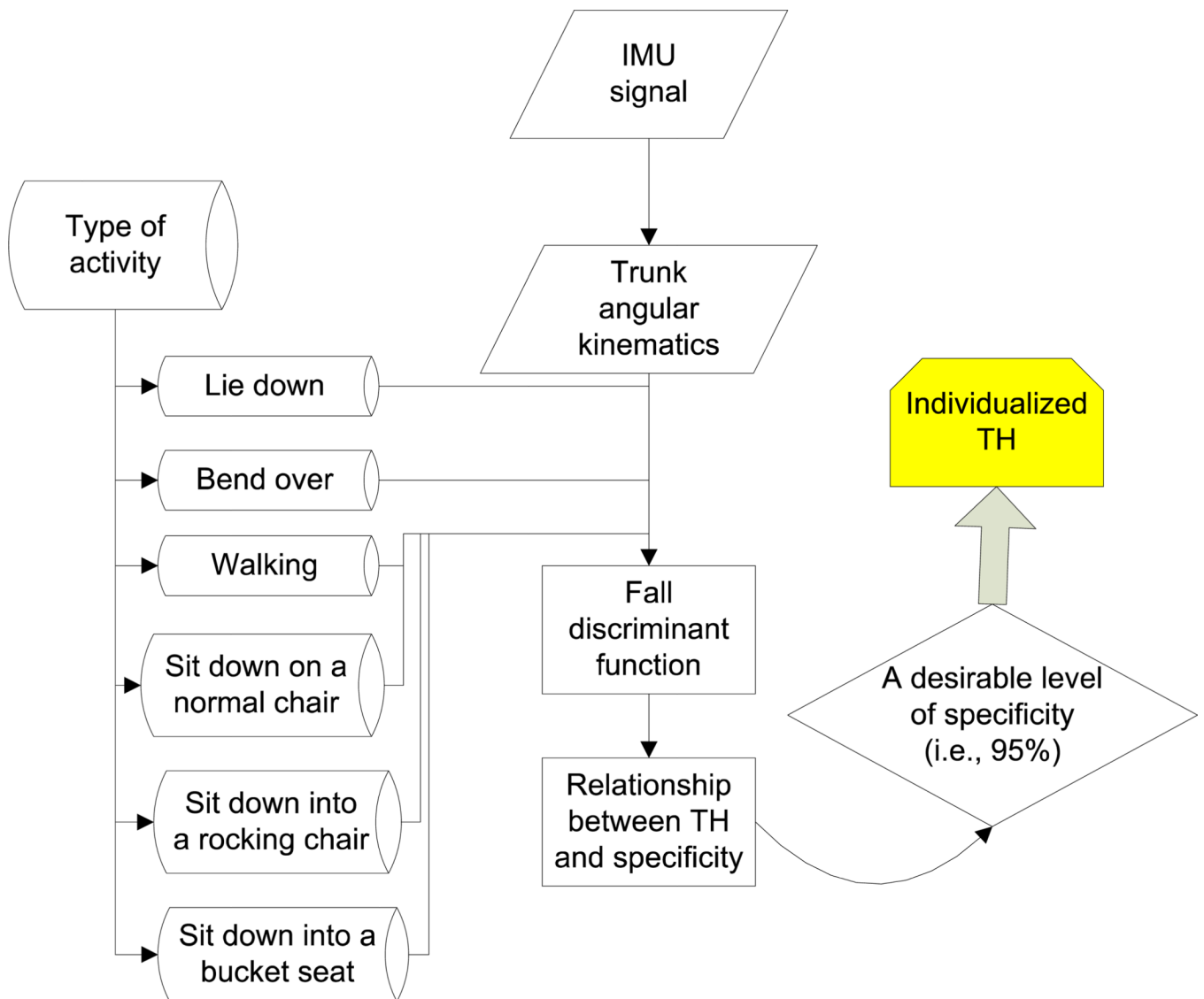Illustration of the IAM framework in fall detection scenario

**Figure 2.**
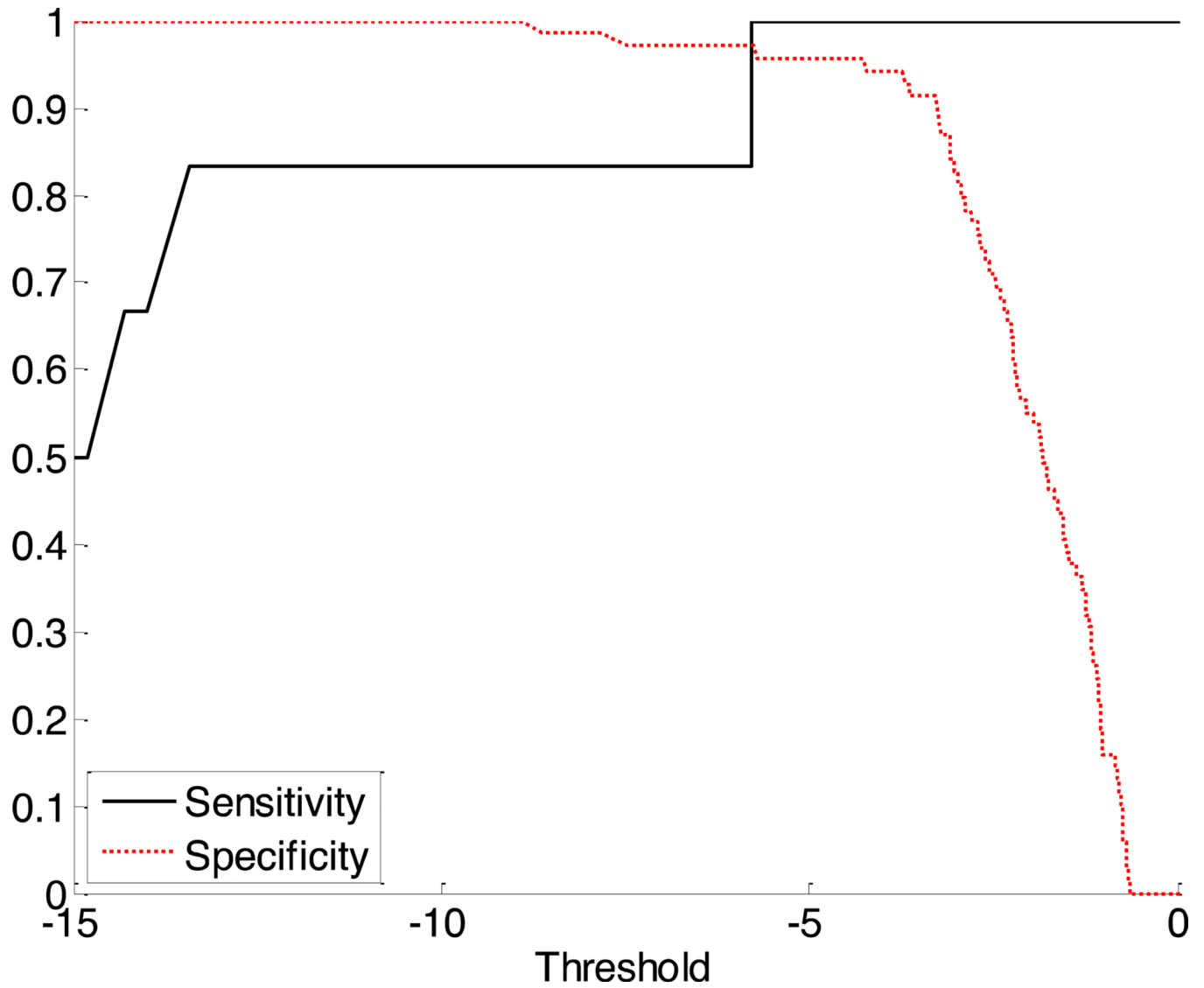Analytical scheme of individual calibration

**Figure 3.**
Influence of fall detection thresholds (TH) on sensitivity and specificity

**Table 1**

Fall detection thresholds (TH) pre and post individual calibration

| Participant # | Detection threshold (TH) | |
|---|---|---|
| | Pre | Post |
| O01 | −4.994 | −4.994 |
| **O02** | **−4.994** | **−2.8855** |
| **O03** | **−4.994** | **−3.8666** |
| O04 | −4.994 | −4.994 |
| O05 | −4.994 | −4.994 |
| O06 | −4.994 | −4.994 |
| O07 | −4.994 | −4.994 |
| **O08** | **−4.994** | **−3.5786** |
| O09 | −4.994 | −4.994 |
| **O10** | **−4.994** | **−2.7634** |