Piecewise Linear Dynamical Model for Actions Clustering from Inertial Body Sensors with Considerations of Human Factors

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ABSTRACT

The efficacy of many Body Sensor Network (BSN) applications relies on the accurate temporal clustering of human motion into actions on various time scales. This is typically done with the use of inertial sensors and processing algorithms that try to extract such information from the sensor data. Two human factors in real-world deployments make such information extraction challenging: mounting errors (where sensor displacement and orientation do not match what is assumed by processing algorithms) and insecure mounting (where sensors are loosely worn causing them to shake during operations).

In order to enhance the robustness of human actions clutsering from real-world BSN data, this work leverages dynamical systems modeling with the considerations of human factors. By proposing a computational body-model framework called the piecewise linear dynamical model (PLDM), we derive a robust method to segment time series data of inertial BSNs in real-world deployment with human factors into motion primitives and actions. We test the proposed method on two different inertial BSN datasets and extract actions on different temporal scales. The experimental results demonstrate the effectiveness of our approach.

Categories and Subject Descriptors

J.3 [**Life and Medical Sciences**]: Health, Medical information systems.

General Terms

Algorithms, Measurement, Performance, Experimentation, Human Factors, Verification

Keywords

Time series clustering, human motion analysis, inertial body sensor networks, linear dynamical system, stimulus point detection.

1. INTRODUCTION

In recent years, inertial body sensor networks (BSNs) that can capture, detect, and recognize human motions have attracted much attention from medical researchers and healthcare professionals due to the large number of potential applications in long-term health monitoring systems [1,2]. The efficacy of these systems greatly depends on accurately extracting set of actions from inertial data (an example is shown in Figure 1).

Despite considerable advances [6] in extraction of actions from inertial body sensors and in prototyping and deploying motion recognition systems, two issues make the real deployments difficult: mounting errors (from sensor displacement orientation) [3] and looseness of sensors [4] (we discuss these issues more in Section 2).

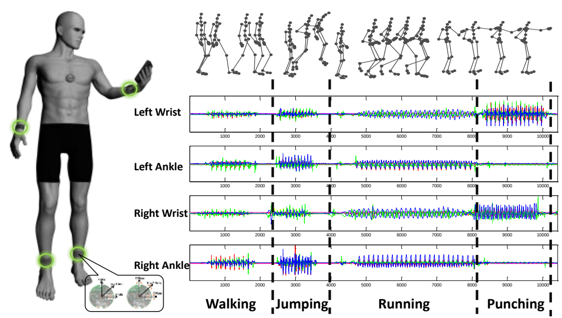

Figure 1. Clustering of inertial BSNs data in hierarchical levels including actions and motion primitives (Table 1). The subject is equipped with four body sensor nodes, which each contains three-axial accelerometer and three-axial gyroscope to capture the acceleration and angular velocity data, on left/right wrists and left/right ankles.

Table 1. Motion primitives in human actions

Walking	Jumping	Running	Punching
Heel Strike (Left/Right)	**Heel Strike (Both)**	**Heel Strike (Left/Right)**	**Punch Forward (Left/Right)**
Toe off (Left/Right)	**Hand Wave (Both)**	**Toe off (Left/Right)**	**Punch Back (Left/Right)**
Hand Wave (Left/Right)		**Hand Wave (Left/Right)**	

In this work, we propose a method, namely the Piecewise Linear Dynamical Model (PLDM) with Motion Stimulus Detection for extracting sets of human actions from inertial data at different time scales which is robust to these two issues. We are able to differentiate at the coarse level between activities like walking, running, and punching, as well as to segment finer parts of actions like walking into heel strike and toe off.

Our insight (detailed in Section 3) reveals that inertial sensor data is the output of a dynamical system (the sensor's dynamics that

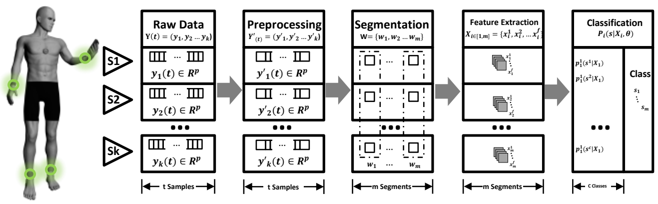

Figure 2. Typical processing pipeline to recognize activities from wearable sensors [6].

transfer physical motion to a measured voltage) driven by stimulus (human actions on the sensor that drive the sensor motion). We evaluate our method (in Section 4) on two sets of inertial data; one that we collected ourselves for extracting coarse actions, and another from Chen et al. [5] which was used in segmenting walking action into finer actions like heel strike and toe off. In both cases we compare to state-of-the-art methods for the particular kind of extraction.

2. BACKGROUND

Typical action extraction or activity recognition systems follow the process illustrated in Figure 2 (adapted from Bulling et al [6]). The raw data is first preprocessed to correct for calibration of sensors and then is segmented. For each segment, features, for instance, mean, variance, or kurtosis, frequency, slope, curvature, duration and co-occurrences of inertial data [6], are extracted. The extracted features may be combined or transformed using a particular function and are then passed to a classifier to determine the particular action.

Many techniques used in the processing pipeline assume that sensors are mounted properly and worn tightly. However, recent studies [4], which investigated the optimal sensor placement when utilizing inertial data to assess physical activity, have revealed that the unknown human factors during deployments of inertial BSNs contribute a major challenge for accurate human action segmentation.

Aiming to achieve more accurate human activity identification from inertial BSN data, this paper considers the human factors associated with the mounting. Specifically, we focus on two main types of human factors during the mounting process of the inertial BSN sensors: mounting error and insecure mounting.

From our empirical analysis, a typical case where mounting errors occur happens when caregivers attach the sensor nodes on the subjects' bodies according to the instructions from engineers or doctors. Instructions such as "on left ankle or right wrist" are followed accurately; however, instructions such as "keep the z axis of the nodes up" result in confusion. If the caregivers incorrectly set up the orientation of the sensor nodes, the data from the inertial BSNs will be totally different from previous deployments because of the mounting error.

In addition, while it is desirable to have inertial BSNs that are tightly affixed to the body to get an accurate signal, the wearability of current sensor nodes is not sufficient, and wearing sensors tightly can be uncomfortable for subjects. This often causes caregivers to loosen the straps of the sensor nodes to put subjects at ease, resulting in insecure mounting. Under these situations, the inertial BSNs will generate much higher noise due to the vibration of sensor nodes, relative to the underlying human motion.

Figure 3 illustrates sample experimental data when inertial nodes are mounted insecurely or incorrectly. Two of the nodes are mounted securely and one is mounted insecurely. The two securely mounted inertial nodes have different orientations on the ankle. The inertial nodes with same orientation have similar signals, while the inertial nodes with different orientations have very different signals. In addition, the insecurely mounted inertial node gains noise from sensor node motion which adds to the body motion in the signal.

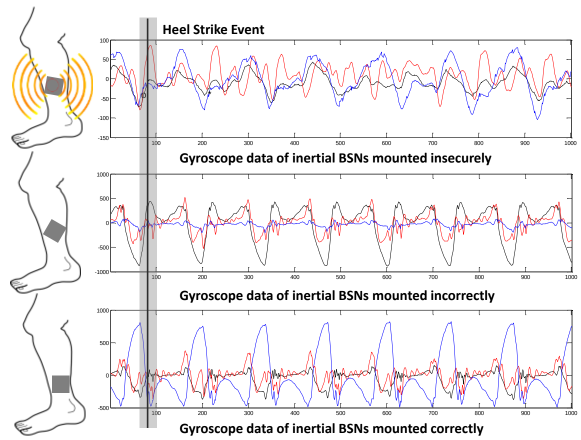

Figure 3. Experimental results of unknown human factors Left picture shows three inertial sensor nodes equipped on left ankle of a subject with their corresponding signals. The bottom two were mounted securely and the top one was mounted insecurely.

Despite the success of various activity analysis algorithms to improve the system performance, most existing algorithms are limited in one aspect: the main requirement for activity analysis algorithms to work well includes that the sensor signal exhibit stable and repeatable patterns. In other words, the signal patterns should exhibit similarity for the same motion within certain tolerant range. However, human factors during the deployment of inertial sensors may cause the signal patterns to become unstable and unrepeatable for the same motion. Therefore, adding the considerations of human factors during the deployment of inertial body sensors should enhance the system performance in real-world deployments.

3. PLDM

For dealing with the effects of human factors during real deployments, we propose a model-driven technique based on dynamical systems. Our main insight is that the process of extracting sets of actions from inertial data is equivalent to developing a state observer for a plant in dynamical systems theory. Using this analogy, the human (plant) can be viewed as a hierarchical control system where at the highest level the person decides to take coarse actions like walk, run, or punch; at the middle level, these coarse actions are translated into sequence of actions (heel strike, toe off, swing phase for walking); and at the lowest level, these sequence of actions are translated into fine-grained controlled movements that are adapted to the environment in which this action is taking place.

The inertial sensors measure these lowest-level movements and since these sensors are also non-linear dynamical systems, we can view the lowest-level movements being measured as stimuli to this sensor system. Our job is therefore to estimate the set of actions (sequence of states) that have produced these lowest-level movements (or stimuli). We must note that in our actual extraction we do not distinguish between the three different levels on the human side. This is because the lower-level movement can be viewed as a representation (signature) of any of the higher levels. This is also why our method works for both coarser and finer set of action extraction.

Based on the previous processing pipeline in Figure 2, Figure 4 illustrates the diagram of the proposed method which integrates the body motion modeling into feature extraction to increase the robustness of handling human factors.

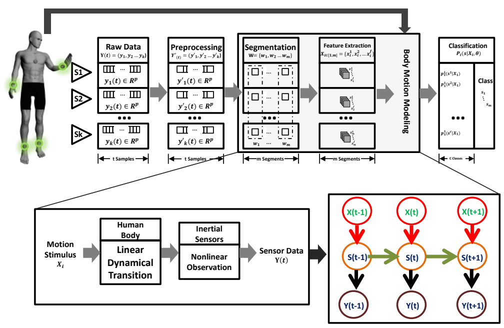

Figure 4. Proposed method integrates the body motion modeling into feature extraction. The body motion is modeled as a hybrid system which contains linear dynamical state transition and nonlinear observation process. Motion stimulus (X_i) is used as extracted features.

3.1 Linear Dynamical Model

Observed human action data from inertial BSNs can be viewed as a multivariate time series. We model such multivariate time series $y(t) \in R^p$ as outputs of a nonlinear dynamical system (the sensor) driven by a one dimensional sparse and bounded stimulus, $x(t) \in R$. Our work is motivated by Raptis' work [7] which holds an assumption of the linearity of the dynamical system. However, since inertial BSNs generally use as sensors accelerometers, which have random transients [9], and gyroscopes, which have random drift [8], a linear model is not ideal for inertial BSNs.

In the past, in order to address the nonlinearities of accelerometers, pre-low-pass filter [3], post signal processing methods [10] and the compensation from other systems such as cameras [11] have been adopted. In addition, in order to model the random drift, nonlinear signal processing methods such as neural networks [12], Kalman filters [13] and cascaded nonlinear models [8] have been used to infer the models. We, however, use a much simpler approach detailed below.

The dynamical system for modeling of human actions with inertial BSNs includes two parts, linear state space transition and nonlinear observation. The linear state space transition is defined by a system matrix $A \in R^{n\times n}$, stimulus matrix $B \in R^{n\times 1}$ and a state vector $S(t) \in R^n$. The nonlinear observation is defined by an observation matrix $C \in R^{p\times n}$ and the probability $P \in R^{p\times 1}$ of the random noise. In the above definition, n describes the order of the linear state space transition of the dynamical model and p is the dimension of the observation. This model is expressed as follows [7]:

$$
\begin{gathered}
||x(\cdot)||_{\ell 0} \leq k \\
|x(t)| \leq 1 \quad \forall t \\
\Sigma_t ||CA^tB||_1 \leq \mu \qquad (1) \\
S(t+1) = AS(t) + Bx(t) \\
y(t) = CS(t) + P
\end{gathered}
$$

where $||x(\cdot)||_{\ell 0}$ is the number of nonzero elements in the stimulus sequence.

An expectation–maximization (EM) algorithm is applied to estimate the A, B, C, S and x matrices under the assumption of system linearity and time invariance. However, in equation (1), the observation matrix C, which being related to the inertial sensors, depends on the mounting position of the sensor, and insecure mounting contributes noise in C (and CS(t) should really be a non-linear function C(S(t))). The probability function of random noise P depends on the physical characteristics of the sensors. In other words, C and P cannot meet the required linearity and time-invariance assumptions, which makes solving the equation intractable.

In order to reduce the complexity of equation (1) and make it tractable, we cut the time sequence $y(t)$into small pieces where each piece contains the non-trivial motion information. With this strategy, we can approximate this nonlinear dynamical system as a piecewise linear dynamical system, since the random noise P and observation matrix C could remain constant for signals of short periods [8]. We therefore require a robust motion stimulus detection method to cut the time series data into pieces with the consideration of potential mounting errors or insecure mounting.

3.2 Motion Stimulus Detection

The initial segmentation of time series data requires robust tolerance of incorrect or insecure mounting. Since PLDM is used to infer the motion stimulus of the system, we can develop a method to detect the moments when the body gets the stimulus.

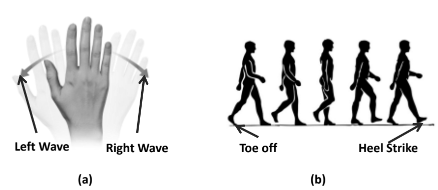

Figure 5. Examples of motion stimulus in human actions. In hand waving, the motion stimulus will be the moments when the hands change its motion direction (a), while the motion stimulus of walking will be the moments will be the moments when heel strikes the ground and the toe get off the ground.

As shown in Figure 5, the motion stimulus of the hand waving action will be the moments when the hand changes its motion direction, while the motion stimulus of walking will be the moments when heel strikes the ground and the toe comes off the ground. This is because in these moments, the human stimuli at the related body parts can cause a dramatic change in positional and/or rotational motion. In other words, the moments of motion stimulus include the salient points in inertial sensor data with remarkable three-dimensional curvatures.

Since the sensor nodes are mounted on the body to capture the motion data, it is reasonable to assume that the motion stimulus does not depend on the mounting condition of sensor nodes on the body.

Recently Olivares et al. [14] conducted a comprehensive study on testing various event detection methods. According to their experimental results, Stance Hypothesis Optimal Detector (SHOD) and Long Term Spectral Detector (LTSD) performed better than others. However, the motion assumption in SHOD cannot match well with the detection requirements of motion stimulus when considering human factors, while LTSD has very high computional complexity. Therefore, based on the definition of motion stimulus, we develop a novel angular rated curvature detector (ARCD) to detect the motion stimulus moments.

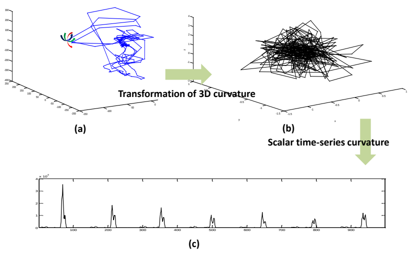

Figure 6. Curvature estimation of (a) time series data of gyroscope in phase space representation. (b) Calculate the individual curvature for each axis of gyroscope and then get the (c) scalar time-series curvature for three axis via a 3D gradient operator.

Because the calculation of curvature of time series data needs to focus on short-term data processing, we prefer to use gyroscope data to determine the motion stimulus because short-term gyroscope data does not have random drift and also does not have random spikes that are often seen in accelerometer data.

Our method is based on Rusinkiewicz [15] who presented a curvature estimation method for triangle meshes. However, it needs high computational complexity and is not appropriate for time series. We therefore simplify the calculation process to estimate the curvature for short-term time-series gyroscope data as follows:

$$\mathrm{Cur_{gyro}} = \nabla_3\left(\nabla_1\left(\nabla_1\left(y\big(t, g(1)\big), y\big(t, g(2)\big), y\big(t, g(3)\big)\right)\right)\right) \quad (2)$$

where $g(\cdot)$is the gyroscope data from an individual axis, $\nabla_n$is the gradient function of n-D signal. From the equation (2), we calculate the individual curvature for each axis of the gyroscope and then get the scalar time-series curvature for three axis via a 3D gradient operator, as shown in Figure 6. The detected motion stimulus corresponds to the peak of the estimated curvature.

Figure 7 shows the preliminary curvature estimation results under different conditions of insecure mounting, incorrect mounting and correct mounting, based on the data from the experiment shown in Figure 2. Since the peaks of the estimated curvature are the detected motion stimulus, as we can see, the peaks of the estimated curvature with mounting errors are almost the same as those with correct mounting. Also, even when sensor node vibration noise is added into the data, the motion stimulus contributed by human actions can be revealed in the estimated curvature. That means, the curvature based motion stimulus detection is robust to mounting errors and is relatively robust to insecure mounting.

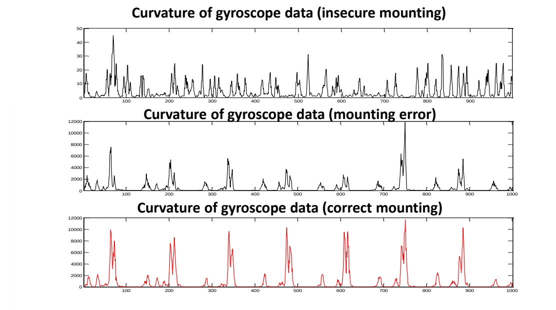

Figure 7. Estimated curvature value of time series gyroscope data under different conditions of insecure mounting, error mounting and correct mounting.

3.3 PLDM Features

We then construct a dynamical model for each piece composed of a window around each motion stimulus. As we discussed earlier in section 3.1, each piece of the human actions can be approximated as a linear dynamical model. Therefore, equation (1) can be rewritten as follows:

$$\begin{gathered} ||x(\cdot)||_{\ell 0} \le k \\ |x(t)| \le 1 \quad \forall t \\ \Sigma_t \left|\left|CA^tB\right|\right|_1 \le \mu \qquad (3) \\ S(t+1) = AS(t) + Bx(t) \\ y(t) = CS(t) \\ 0 < t < t_\ell \end{gathered}$$

where observation matrix C is a time-invariant matrix in the short period of each piece, and $t_\ell$is the length of each piece. Based on EM algorithm, we caculate A , B, C and S with an initial given x, then refine x based on the initial estimated A, B, C and S, and repeat the EM process until the cost function converges (Figure 8 shows the pseudo code of EM algorithm). After the model construction via EM algorithm, we can get the estimated stimulus vector for each piece of the linear dynamical model, $x(t), (0 < t < t_\ell)$. For more information about the EM algorithm, we refer the reader to [7].

To construct a PLDM feature, we detect the motion stimulus as in Section 3.2 from available sensor nodes. Second, we utilize PLDM to model each piece from each sensor node to generate the stimulus vector $x(t)$. Third, we construct histograms of the stimulus vectors. Each histogram is quantized into 11 bins, equally spaced in a range from -1 to 1. Finally, to encode information from the stimulus to the articulated body, the histograms for multiple sensor nodes are stacked together to create a descriptor of human motion at each motion stimulus. Figure 8 shows an example of PLDM feature extraction process.

3.4 Hierarchical Temporal Clustering

Based on the representation of the articulated body motion, this section describes how to build the feature set for different temporal scales in a hierarchical manner, because the segmentation of human actions requires considering different temporal scales for different purposes.

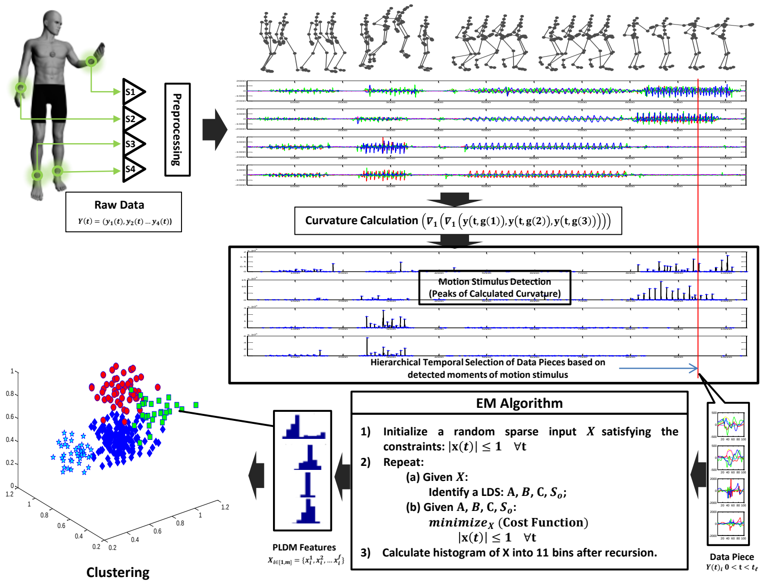

Figure 8. Diagram of PLDM feature extraction and clustering process. Motion stimulus detection initially segments the time-series inertial data into pieces. Data pieces can be selected hierarchically from different temporal scales which depend on our clustering purpose. Selected data piece feeds into EM algorithm to estimate motion stimulus. Based on a local linear dynamical model, combined motion stimuli are used as PLDM features in next-step clustering.

For the coarse level of the segmentation of human actions, such as recognition of walking, running, and other types of behaviors, we can combine all the estimated curvatures from all sensor nodes to detect the motion stimulus, and then generate the feature set. For the fine level of the segmentation of human actions, such as recognition of walking motion events such as heel strike and toe off, we can focus on the time series data from sensor nodes mounted on the ankles, detect the motion stimulus and then generate the feature set.

Next, we perform temporal clustering to convert hierarchical features into action clusters (Figure 8 shows the hierarchical temporal selection process from the data pieces set). For the temporal clustering, we use the lossy coding approach of [16] to produce an optimal unsupervised segmentation. At the final step, the user will be able to look over the clustering results and label each cluster as name of the actions.

Given the feature set by our algorithm, this full segmentation procedure takes approximately 1 minute on a set of 1000 pieces.

4. EXPERIMENTAL RESULTS

We conducted two experiments to demonstrate the ability of our PLDM-based technique to segment actions at both fine and coarse time scales. In each experiment we have compared the segmentation performance to another state-of-the-art algorithm for doing particular scale segmentation. The choice of algorithm was based on the ability to perform a fair comparison.

4.1 Coarse Level Clustering Experiments

In this experiment, six natural actions (straight walking, running, jumping, sideways walking, punching, and body rotation) were performed in sequence with short breaks between two continuous actions. Each subject wore four inertial sensor nodes (on the left and right wrist and left and right ankle). Each action sequence was repeated for three times under different mounting conditions: correct mounting, mounting with displacement error, and insecure mounting. The sampling rate of the inertial sensors is 128Hz, and the length of time series data (for one sequence of six actions) ranges from 3 minutes to 5 minutes.

Figure 9 shows the segmentation results obtained through (1) PLDM, (2) manual labeling (ground truth was accounted by manual stopwatch), and (3) the aligned cluster analysis (ACA) method proposed by Zhou et al. in [17] for both subjects. Different actions in the sequence are marked with different colors. The gray stripes in the ground truth sequences indicate areas where the judgments vary among labels or no judgments at all, because our hypothesis in PLDM is that if there is no motion stimulus in the human motion, that particular segment belongs to "no movements at all." PLDM and ACA both work well under the correct mounting condition; however, actions identified by PLDM are closer to manual labeling than those from the ACA method under incorrect mounting conditions. The ACA method fails to identify actions with insecure mounting. In fact, according to experimental results in [17], the ACA method should be reliable in the incorrect mounting condition under secure mounting. However, in reality, mounting errors are always accompanied by insecure mounting, which ACA could not handle well.

Choosing ACA as the baseline is because ACA was the only method we found to be action-label-definition-agnostic. In other previous action clustering or recognition methods [6, 18, 19], the experimenters determine the labels for the actions, and their implicit definition of actions may differ from ours. Since we do not have access to their datasets it is unfair to measure their methods with labels whose definitions may differ from the ones on which those methods were originally developed.

4.2 Fine Level Clustering Experiments

The second experiment is based on the dataset used by Chen et al. for multiple sclerosis [5]. Here the goal is to identify the "heel strike" and "toe off ground" points in data from 6-minute walks by subjects. This finer time scale action extraction is used to measure various properties of gait in order to identify disorders in the gait patterns. The data consists of 44 sequences from 27 subjects (some subjects contribute several experimental sequences). Each subject wore five inertial sensor nodes similar to those in our previous experiment (at the same four locations as the previous experiment but with hip as additional location).

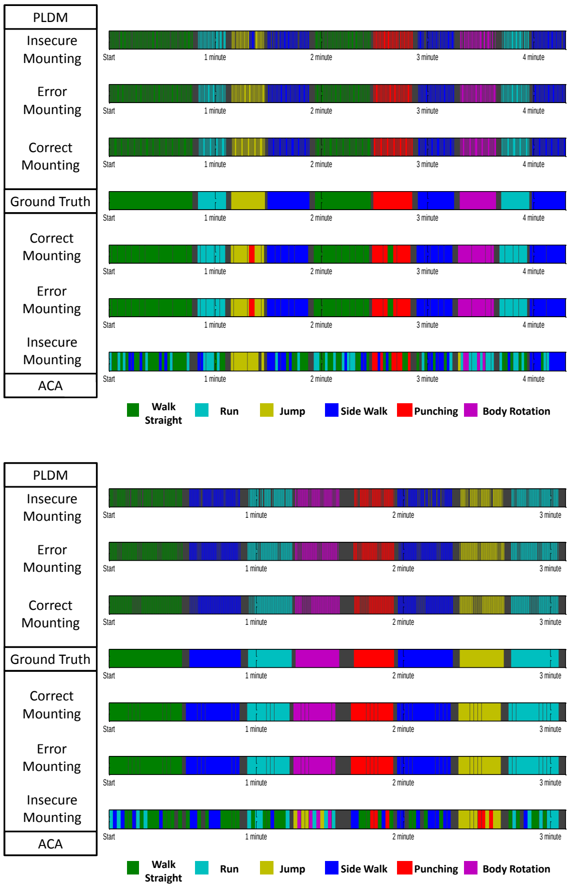

Figure 9. Clustering experiments by PLDM and ACA. Ground truth is captured by stop watch manually, where gray lines indicate the boundaries of actions. For PLDM and ACA, the gray lines show the composition of cyclic movements. The different colors correspond to different actions.

Figure 10 and Figure 11 show a comparison of event detection performance between the PLDM and the method from Chen et al. [5] on the 44 sequences. We should mention that the threshold used by [5] in detecting the peak of the motion events can be adjusted to fit the variability in the time series data. This adjustment requires extensive manual analysis, and we adopted its default threshold, same as the method in [5]. We expect that average, a person takes two steps in a second (one for each leg) [20]. With some variance, this would mean the number of pairs of events should range from about 300 to about 400 for a six-minute walk sequence. In general, PLDM indicates more motion events occur in each sequence than Chen at al.'s method and the PLDM values are within the expected range whereas the Chen et al.'s method indicates a very small number of events [5] and a fewer number of events overall.

We compared to Chen et al because we had access to their original data and code for identifying the various events, though we did not have access to ground truth for the events.

5. RELATED WORK

As mentioned earlier, recognizing sets of actions in human motion is an important component of using inertial BSNs for monitoring and hence there has been quite a bit of work along this path. Bulling et al. [6] provided a tutorial with a comprehensive review of activity recognition methods. They developed a general framework for understanding the signal processing pipeline of these methods called the Activity Recognition Chain (ARC), which is a useful framework for researchers new to the field.

Some of the notable methods identified in this survey include the use of template-based similarity metrics such as dynamic time warping (DTW) [17], or Principal Component Analysis (PCA) [21], and probabilistic methods like hidden Markov models (HMMs) [21], or statistical models [22] which are used to handle temporal dependencies in the data. In addition, discriminate approaches like support vector machines (SVMs), or decision fusion have been successfully applied in a number of activity recognition scenarios.

Several previous studies have also incorporated some model of body motion into the recognition scheme. Zinnen et al. [18] introduced their particular body model into motion primitives (the feature extraction stage) such as upper arm, lower arm bending and rotation. Zhang et al. [19] developed a bag-of-features (BoF) based method to describe the body motion model.

The main drawback of these techniques is the assumption that similar body motions will produce similar signal patterns, which does not hold in real deployments because of the issues of human factors, such as mounting errors and insecure mounting that our work tries to address.

Otherwise, recent study [23] shows that model driven method can be used to address the issue of mounting errors. Our work takes it further in the considerations of human factors during the real-world deployment of inertial BSNs.

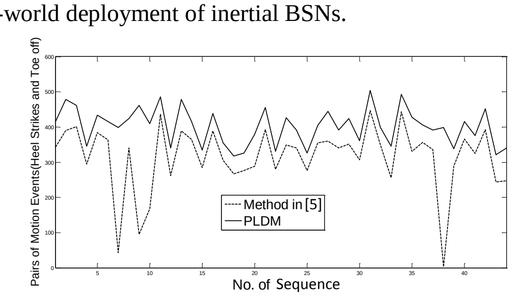

Figure 10. Experimental results of events detected by PLDM and method in [5] from walking scenarios. A pair of events during walking contains "heel strike the ground" and "toe off the ground", which are the non-trivial motion stimulus in human walking actions.

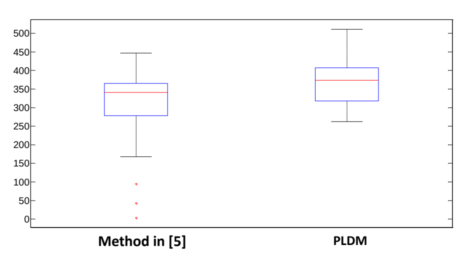

Figure 11. Comparison of events detected by PLDM and method in [5] from walking scenarios.

6. Conclusion

In this paper, we propose PLDM, a technique that leverages dynamical system modeling with temporal clustering for the segmentation of human actions from time series data generated by the inertial BSNs. The main novelty comes from that PLDM combines a robust motion stimulus detection algorithm with a modified linear dynamical model. The motion stimulus detection algorithm is designed to solve challenges such as the inherent sensor errors of inertial BSNs and unknown human factors (mounting errors and insecure mounting) during the deployment of inertial BSNs. We have compared PLDM to state-of-the-art algorithms for different temporal-scale applications where PLDM has achieved better performance.

Future work focuses on refining the PLDM, such as reducing the computational complexity of modeling process, optimizing the clustering process of human actions and exploring other applications.

7. ACKNOWLEDGMENTS

Our thanks to Asma Qureshi, Dawei Fan, Shanshan Chen, and Dr. Myla D. Goldman for collecting the experimental dataset.

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