Healthcare Algorithms by Wearable Inertial Sensors: A Survey

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Abstract: Wearable smart devices, such as smart watch, wristband are becoming increasingly popular recently. They generally integrate the MEMS-designed inertial sensors, including accelerometer, gyroscope and compass, which provide a convenient and inexpensive way to collect motion data of users. Such rich, continuous motion data provide great potential for remote healthcare and decease diagnosis. Information processing algorithms play the critical role in these approaches, which is to extract the motion signatures and to access different kinds of judgements. This paper reviews key algorithms in these areas. In particular, we focus on three kinds of applications: 1) gait analysis; 2) fall detection and 3) sleep monitoring. They are the most popular healthcare applications based on the inertial data. By categorizing and introducing the key algorithms, this paper tries to build a clear map of how the inertial data are processed; how the inertial signatures are defined, extracted, and utilized in different kinds of applications. This will provide a valuable guidance for users to understand the methodologies and to select proper algorithm for specific application purpose.

Keywords: healthcare; algorithms; wearable; inertial sensors; IMU; gait analysis; fall detection; sleep monitoring

I. INTRODUCTION

The market size of wearable devices are growing very quickly. In a recent report by BusinessInsider[1], the global annual wearable device unit shipments have just crossed 100 million milestone in 2014. In a more recent market research, ABI Research[3] pegs the wearables market at 485 million annual device shipments by 2018. On the other hand, the price of wearable devices is going down very fast. Now, the price of some topnotch wristband is as low as 13 US dollars[4], while providing great functions such as activity analysis and sleep monitoring. Booming of these two trends will lead to a new revolution, that the wearable devices will be increasingly popular to become a part of our life.

The wearable devices are working not only as accessory equipments of smart phones, but also as sensors to track user's body states, and as interface in human-computer interaction. These functions are mainly benefited by the embedding of MEMS sensors. Although many kinds of MEMS sensors, such as blood pressure etc, are used in wearable devices, the most widely used sensors are the inertial measurement unit (IMU). An IMU is as tiny as 5*5 millimeters and is as cheap as one US dollar[19]. But it integrates 3D-accelerometer, 3D-gyroscope, and 3D compass, which provides rich and continuous motion data of the user who is wearing the device. These rich motion data contains fruitful clues about the user's body states and health states. Therefore, enormous efforts have been attracted to investigate the wearable inertial sensor data for body state monitoring and health state monitoring. Among all these investigations, algorithms play the critical role, which process the inertial data to extract features and to make judgement based on the extracted features. This survey focuses on the healthcare applications, and reviews related works form an algorithm perspective.

Existing applications based on wearable inertial sensors mainly contain two categories: 1) activity-related applications; 2) healthcare-related applications. The activity-related applications use inertial sensors to monitor daily activities of users, ranging from step counting, exercise statistics, gesture recognition, to indoor navigation etc. Key algorithms in this area include zero velocity update (ZUPT)[48], zero angle rate update (ZARU) [23], dead reckoning etc[37]. Since thorough surveys of these algorithms can be found in recent work[48], we will not go into details of these activity-related algorithms in this paper. In stead, this paper focuses on the algorithms for healthcare-related applications. Many works have been done on health sensing[53] [49][32], a common feature of these algorithms is that they generally involve a data processing, feature extraction and a judgement process. They use the inertial sensor sequence as input, and output the diagnosis result or alarms of emergency. In particular we focus on three areas: 1) gait analysis; 2) fall detection, and 3) sleep monitoring. Representative algorithms will be reviewed, classified, and compared. The architecture of wearable inertial sensor based applications and the focus of this paper is highlighted in Fig.1.

The remained sections of this paper are organized as follows. The characteristics of inertial sensors, in particular, the coordination systems of the inertial sensors are introduced in Section II. The gait analysis algorithms are introduced in Section III, with fall detection algorithms and sleep monitoring algorithms reviewed in Section IV and V. The paper is concluded with discussion in Section VI.

This paper presented an in-depth and thorough review on algorithm aspect of health monitoring methods by wearable inertial sensors.

II. Characteristics of MEMS Inertial Sensors

By inertial sensors, we refer mainly to accelerator, gyroscope and compass sensors. Historically, they are widely used in aerospace and marine navigation. Nowadays, the advantage of MEMS technology has enabled tiny, low cost, MEMS-designed inertial sensors, i.e., Inertial Measurement Unit (IMU). The size of an IMU can be as small as 10mm*10mm*4mm, and with cost less than 1 USD[48]. It integrates 3-axis accelerator, 3-axis gyroscope and 3-axis compass. Such embodiment of IMU enables motion sensing by wearable devices, which is the foundation of wearable computing.

1) Accelerometer: Accelerometer measures the acceleration of in a relative coordinate system of IMU without an external reference. Different by types, accelerometer can measure acceleration in one, two, or three orthogonal axes. For a tri-axis accelerometer, it measures:

$$a = \{a_x, a_y, a_z\} \tag{1}$$

2) Gyroscope: Gyroscope measures the angular velocity expressed in Cartesian coordinates:

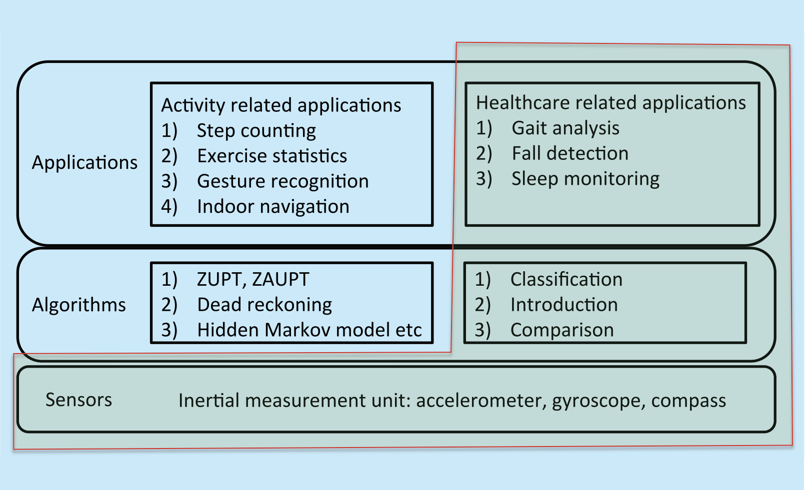

Fig.1 *The focus of this paper is highlighted*

$$w = \{w_x, w_y, w_z\} \quad (2)$$

which produces a positive measurement value for counter-clockwise rotation around the sensitive axis considered. The measurements are relative to the sensor's own coordination system.

3) Compass: Compass is an orientation measurement tool, which measures orientation is in geodetic coordination system.

2.1 Orientation System of IMU

A basic problem in using inertial sensor is the orientation system transformation between the IMU body and the global orientation system. The global orientation system is called inertial frame, which is a global, earth-fixed frame, as shown in Fig. 1. It uses North as x-axis; East as y-axis and Down as z-axis. The IMU body frame is the coordinate system that is aligned with the body of the sensor. The x-axis points to the front direction of the sensor; the y-axis points to the right side and the z-axis points to the bottom of the sensor, as shown in Fig.2. Euler Angles[6] are used to describe the orientation of the IMU body relative to the inertial-frame. The Euler Angles represent rotations of IMU in three axises in the inertial frame, which are called Roll (φ), Pitch (θ), Yaw (ψ) angles respectively.

1) Rotation matrix: If only yaw rotation happens, the inertial-frame rotates the yaw angle ψ in its $x-y$ plane. This create a new coordinate frame, which is called vehicle-1 frame. Rotation a vector from the inertial frame to the vehicle-1 frame can be performed by multiplying the vector by a rotation matrix:

$$R_I^{v_1}(\psi) = \begin{pmatrix} \cos(\psi) & \sin(\psi) & 0 \\ -\sin(\psi) & \cos(\psi) & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

When both yaw and pitch happens, the vehicle-1 frame rotates an angle θ in vehicle-1 frame's $x-z$ plane. This forms a new coordination frame, called vehicle-2 frame. The rotation matrix for moving from the vehicle-1 frame to the vehicle-2 frame is given by:

$$R_{v_1}^{v_2}(\theta) = \begin{pmatrix} \cos(\theta) & 0 & -\sin(\theta) \\ 0 & 1 & 0 \\ \sin(\theta) & 0 & \cos(\theta) \end{pmatrix}$$

The body frame is obtained by performing a rotation by the angle φ in the vehicle-2 frame's $y-z$ plane. The rotation matrix for moving from the vehicle-2 frame to the body frame is given by:

$$R_{v_2}^{B}(\phi) = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos(\phi) & \sin(\phi) \\ 0 & -\sin(\phi) & \cos(\phi) \end{pmatrix}$$

The complete rotate matrix for moving from the inertial frame to the body frame is given by:

$$R_I^B(\phi, \theta, \psi) = R_{v_2}^B(\phi) R_{v_1}^{v_2}(\theta) R_I^{v_1}(\psi)$$

The rotation matrix from the body frame to the inertial frame is given by

$$R_B^I(\phi, \theta, \psi) = R_I^{v_1}(-\psi) R_{v_1}^{v_2}(-\theta) R_{v_2}^B(-\phi)$$

2) Get pitch, roll, and yaw from accelerometer and compass: Since the accelerometer counters the gravity when at rest, it measures $1g$ on its z-axis and 0 on x and y axes when pitch and roll are zero. When pitch and roll are not zero, the x-axis and y-axis experience a component of upward acceleration, which depends on the tilt angle.

So the pitch and roll angles can be inferred from the accelerometer readings.

$$\theta = \arctan\left(\frac{a_y}{\sqrt{a_x^2 + a_z^2}}\right), \phi = \arctan\left(\frac{-a_x}{a_z}\right)$$

To obtain the yaw angle, i.e., to know the heading direction of the IMU body, we need to use both the accelerometer and the compass data.

$$X_h = X_m \cos(\theta) + Z_m \sin(\theta)$$

$$Y_h = X_m \sin(\phi)\sin(\theta) + Y_m \cos(\phi) - Z_m \sin(\phi)\cos(\theta)$$

where X_m, Y_m and Z_m are magnetic sensor measurements. Then the yaw angle, i.e, the heading angle can be estimated by:

$$\psi = \begin{cases} \pi - \arctan\left(\frac{Y_h}{X_h}\right), & \text{if } X_h < 0 \\ -\arctan\left(\frac{Y_h}{X_h}\right), & \text{if } X_h > 0 \text{ and } \mathrm{Y}_h < 0 \\ \pi - \arctan\left(\frac{Y_h}{X_h}\right), & \text{if } X_h > 0 \text{ and } \mathrm{Y}_h > 0 \\ \pi/2, & \text{if } X_h = 0 \text{ and } \mathrm{Y}_h < 0 \\ 3\pi/2, & \text{if } X_h = 0 \text{ and } \mathrm{Y}_h > 0 \end{cases}$$

2.2 Noise Characteristics

Because the low-cost and MEMS design, the embedded IMU has ignorable measurement noises, which affect the state monitoring accuracy. Existing works investigated the noise characteristics of the MEMS-designed IMU. A widely used tool to investigate the error characteristics is the Allan variance. The Allan variance (AVAR)[5], also known as two-sample variance, is a measure of frequency stability in clocks, oscillators and amplifiers, which reveals the characteristics of error in different time scales.

In [15] El-Sheimy et al. presented analysis and modeling of inertial sensors using Allan Variance. It shows that the quantization noise is the prominent error term in the short cluster times, whereas it is the drift rate-ramp term in the long cluster times. In [56], Zhang et al. presented an allan variance analysis on the error characteristics of gyroscope sensors. They showed that the quantization noise is the dominant error in gyro data in short time scale and the rate random walk noise is the dominant error in long time scale. In [8], Bistrov also presented allan variance analysis to the IMU measurements and presented stochastic model to reduce the measurement errors. In [24] Shiau et al. investigated the null drift of MEMS gyroscope and temperature compensation. They showed that the null voltage measurements demonstrated the rapidly changing short-term random drift and slowly changing long-term drift due to temperature variations. A temperature calibration mechanism was established by using an artificial neural network to compensate the long-term drift.

III. Healthcare by Inertial Sensors

After introducing the orientation system and error characteristics of IMU measurements, let's focus on the algorithmic aspect of using IMU measurements for healthcare. We will investigate three areas: 1) gait analysis; 2) fall detection; and 3) sleep sensing.

3.1 Gait Analysis

Gait analysis is aiming at measuring gait parameters, which is informative for clinic diagnosis such as stroke and PD (Parkinson's disease).

1) Gait parameters: Existing work detected different gait parameters for healthcare purpose:

1. Cadence: i.e, the number of steps per minute [60].
2. Swing/Stance Radio (SSR)60]: which is the average swing time (T_{sw}) over stance time (T_{st}), i.e. $SSR=T_{sw}/T_{st}$.
3. Step length[44]: preceding distance of a step.
4. Stride length[44]: preceding distance of a stride circle
5. Stride width[44]: the separation between two feet's centroid.

These parameters are utilized to analyze the step regularity, which can be used for disease diagnosis and user recognition. These gait parameters are generally measured by foot-mounted or leg-mounted IMU.

2) *Parameter measurement:* Foot-mounted IMU can measure motion of foot in both on-land and off-land stage, which is used in many works [34][35]. To extract gait parameters, analysis on both time domain and frequency domain is involved.

i. By time domain gait parameter analysis: In time domain, state of foot is cycling from on-land and off-land, i.e., from stances to swings, separated by Toe-off and Heel-strick points. A widely accepted assumption [48] utilized for stride cycle detection is the

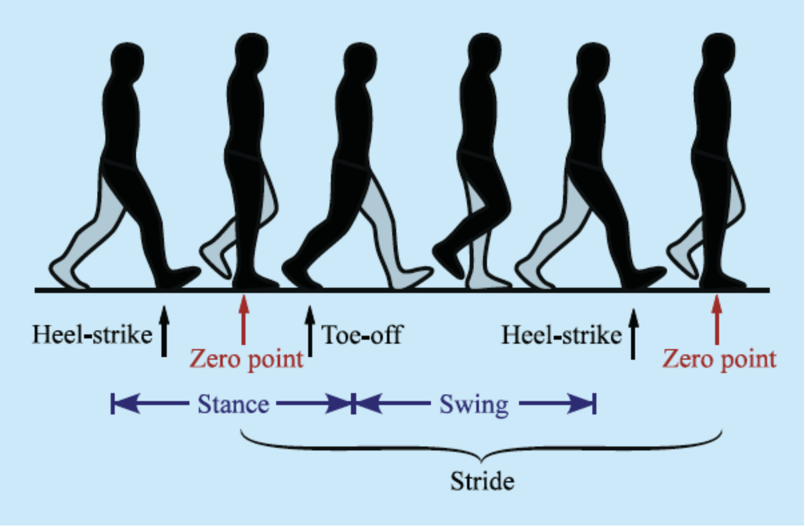

Fig.2 *Gait parameters[61]*

"zero velocity'' at the stance phase, where the acceleration, velocity and angular rate of the foot-mounted IMU can all be regarded as zero. The zero points can be detected by thresholding the acceleration to find the points closest to zero[60]. The interval between two "zero points'' is a stride cycle to analyze the gait parameters.

1) Cadence: After detection the stride cycle, the cadence can be calculated by $c = 120 * \frac{f}{n}$, where f is the sampling frequency and n is the average number of samples in the stride cycle.

2) SSR: In a stride cycle, after detecting the toe-off and the heel-strike points, the SSR can be calculated directly by $SSR=T_{sw}/T_{st}$, where T_{sw} is the interval from toe-off to heel-strike and T_{st} is the interval from heel-strike to toe-off.

3) Stride Length/Step length is calculated by the integral of velocity over the period of a stride cycle. $s = \int_0^T v(t)dt = \int_0^T \int_0^t a_h(\tau)d\tau dt$, where T is the length of a stride cycle.

ii. By time-delay embedding based gait analysis: Since motion of feet is a cycle between on-land and off-land, state of foot at time t can be estimated according to previous m observation before t. At the same time, we assume the dynamic of feet is controlled by a k-dimension hidden state. Using m observation to estimate k state is actually a $\mathcal{R}^m \to \mathcal{R}^k$ mapping, which is referred as time-delay embedding [16]. In [16], Frank et al. presented Geometric Template Matching method. The accordance between the gait parameters and the IMU's readings are be scored. By going through all feasible motion models, the suitable time-delay embedding can be found. In this way, the gait parameter is estimated.

iii. By hidden markov model: Some other approaches presented hidden Markov model for gait analysis[22], [36]. The feature points in a step are recognized as states and training of the state transition model and the observation model are applied by labeled data set. Then the gait segments[30], [42] are recognized by the hidden Markov model to improve the robustness of stride cycle detection.

iv. By other machine learning methods: Other machine learning algorithms were also investigated in gait analysis [7], [11], [59], [57]. In [57], Zhao et al. presented classification algorithms including C4.5 decision tree algorithm, Bayesian classification algorithm and clustering algorithm EM to classify lower limb motions by gait parameter analysis. In [7], Begg. et al. presented support vector machine (SVM) for the automatic recognition of gait changes due to aging using three types of gait measures: basic temporal/spatial, kinetic and kinematic. In [59], SVM, KStar and Random Forest algorithms were presented to classify patients by gait parameters to three kinds of diseases. In [11], Chan et al. investigated Multilayer Perceptron (MLP), KStar and SVM algorithms to accessing gait patterns of younger and older healthy adults climbing stairs.

3) Applications of Gait Analysis:

i. Disease diagnosis: The relation between gait parameters and disease is obtained by empirical modeling. Gait parameters of person with and without certain disease is sampled. Caused by the disease, gait parameter shows different distribution over healthy subject and subjects with disease. This distribution character is used as classifier. So far classifier for Parkinson's disease(PD) [46] and Stroke has been developed[29]. In [59], gait parameters were utilized in machine learning algorithms to discriminate three kinds of diseases, namely Amyotrophic lateral sclerosis, Parkinson's disease and Huntington's disease. By these techniques, disease diagnosis can be achieved on top of cheap IMU instead of the professional device in the lab.

ii. User recognition: Because different people have different patterns in the way of walking, gait parameters can be utilized as for user recognition[16]. As a typical classification problem, measured parameter is compared with all labeled parameter to find the close one as identification result. In [16], a motion model is trained by each labeled gait parameters set. Applying this model to every other observation, we can get a score to quantify the correlation between two gait sequence. In this way, the pairwise similarity of every person is obtained. In [31], user identification is achieved in a more straightforward way. For each user, a segment of motion in walking state is recored as reference. By comparing the unlabeled motion data with every labeled one, identity of user can be estimated.

In summary, parameter measurement is the key in gait analysis. Based on the measured parameters, both user's healthy state even user recognition can be carried out. This enables some novel clinic and security applications.

3.2 Fall Detection

1) Fall Detection Intention: Fall detection tries to detect fall fast and accurately in daily environment. Wearable sensors or smartphone that bear accelerometer, gyroscope, etc. vary in sensor type, placement, device, quantity and approach (Table I) have been extensively studied. Fall detection system is usually evaluated by false negative (FN) and false positive (FP), which FN means a fall occurred while the algorithm could not detect and FP means a fall is not occurred while the algorithm report a fall event.

2) Fall Detection by Thresholding: Capturing the accelerometer sensor changes are the main approaches to detect falls, and many heuristic designed algorithms based on thresholding are proposed.In many work [10][9][51], thresholding on intensity of acceleration is used as a character to detect fall, which is based on an assumption that acceleration in fall process is more fierce than the acceleration in ADL state.

i. By thresholding inertial sensor I: Bourke[9] et al. presented how to use wearable IMU sensor and simple thresholding to judge fall. Since there are multiple channels in IMU, multiple thresholding values are required.

Figure 3 show the contrast between ADL and falls on several channels. In general, reading exceeds threshold value on every channel. Let I_i refer to the thresholding indicator on the ith channel. Then the thresholding of a fall can be indicated by I, which is the logic AND of the indicator on every channel:

Table I *Fall detection algorithm overview*

Algorithm prerequisite	Content
Sensor Type	Accelerometer, gyrometer
Placement	Wrist, chest, belly, thigh, foot, etc.
Device and type	Wearable sensor tag, smartphone
Sensor quantity	1~5
Approach	Threshold detection, machine learning, phase detection [27]

$$I = \bigwedge_i I_i \tag{3}$$

Obviously, definition of I minimizes probability of false alarm but somehow loses the sensitivity. Figure 3 shows the effect of thresholding. Different row of the figure shows the readings of IMU on different channel, where RSS is Root-Sum-of-Squares of the tri-axial accelerometer signal, RSS_d is dynamic RSS and $V_v e$ is vertical velocity estimate [10]. Different columns show the readings formed by different activities. It can be found that, in almost all channels, thresholding on the individual channel is enough to distinguish fall from ADL. When the joint indicator in (3) is applied, the ratio of false alarm is reduced.

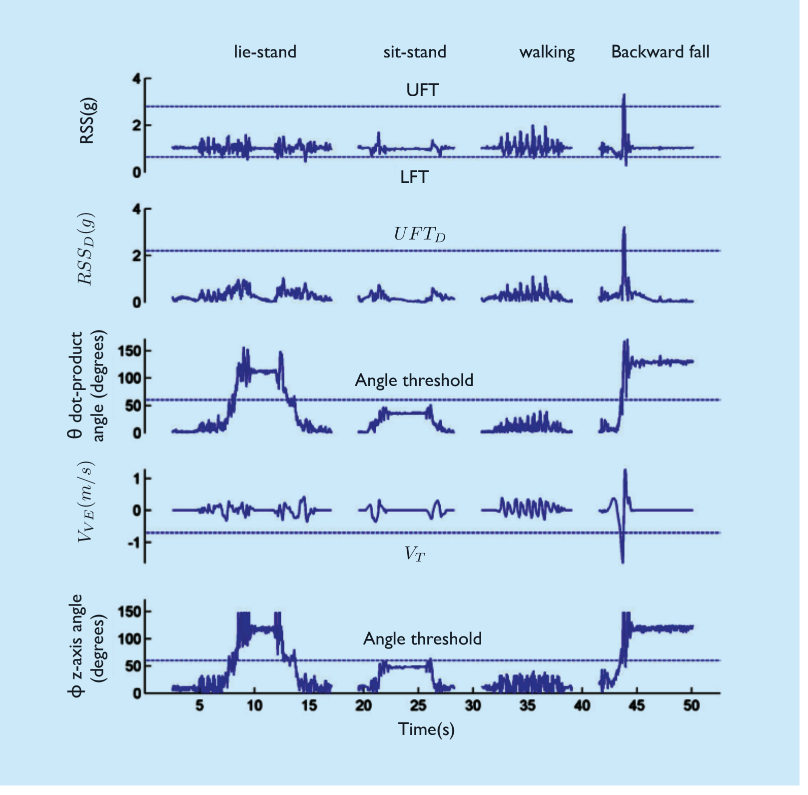

Fig.3 *Thresholding on multiple channel in IMU[10]*

ii. By thresholding inertial sensor II: Chen et. al. [12] introduced sensor motes that were attached to both belt and worn around the waist to detect fall. First, the algorithm detects if the acceleration exceeds a threshold which is caused by the impact of a fall. Second, it will check that the orientation before and after the impact within a small window is changed to assure a fall is occurred. The algorithm set the parameters such as window size, thresholds, etc. empirically, and if the interval between two impacts are too close, second step would not be triggered in order to reduce false alarm. Srinivasan et. al. [51] uses a similar method but check the orientation with a different way.

iii. By combining phase detection: Li et. al. [27] proposed a three phase model to detect fall. In the system, two accelerometers are placed on the abdomen and the right thigh, and the data stream is segmented into one second window. First phase is to monitor whether the user is static or dynamic, second phase is recognize lying state and the last phase is to determine if the transition is intentional. The author collects typical acceleration amplitude and rotational rate and find it is less than $0.4g$ and 60° respectively. The lying state is recognized by assuring the angle between the trunk and gravitational vector and the angle between the thigh and gravitational vector is larger than a threshold. The final phase of intention check is differentiated by confirming the peak value within a window is larger than the threshold. The algorithm could reduce both false alarm by deriving the posture information from both gyroscopes and accelerometers. A similar method is in RAReFall that was proposed by Gjoreski et. al. [17]. This algorithm measures the difference between maximum value and minimum value within a 1s window, if the difference is larger than 1g and the maximum value is at the back of minimum value then a fall is detected.

3) Fall Detection by Introducing Smartphone: Many works have been done for the fall detection on the smartphone [14][38][47]. Jiapeng et. al. [14] proposed an prototype of Android application PerFallD that detects acceleration in smartphone to detect falls. The algorithm is based on two values: total acceleration of the phone $|A_T| = sqrt(A_x^2 A_y^2 + A_z^2)$ and the acceleration at absolute vertical direction $|A_v| = \left|A_x sin\theta_x + A_y sin\theta_y + A_z cos\theta_y cos\theta_z\right|$. The detection algorithm first check the difference of $|A_T|$ and $|A_v|$ within a window win_1, and if this occurred the algorithm will check whether the difference (maximum and minimum) within another window win_2 that follows win_1 is less than a threshold Th_2; if the condition of two detection steps are satisfied, then the algorithm would report a fall behavior.

4) Fall Detection by Machine Learning Techniques: Learning the pattern of acceleration data when a fall is occurring has been studies widely [28][38][54][55]. Raw data is often pre-processed by low-pass filter, re-sampling. Typical features like mean, variance, standard deviation, etc. are often extracted.

Zhao et. al. [58] proposed FallAlarm on mobile phone and trained three models (decision tree, SVM and naive bayes) based on five features (mean, standard deviation, slope[58], energy and correlation). Luštrek et. al. [28] presented novel approach that makes the user wear up to four tags on the body and the fall is detected by Random Forest classifier. The algorithm sampled accelerometer at 10Hz and statistical features are derived from a 0.8s sliding window. After a greedy feature selection before training a classifier, variance of the length of the acceleration vector, the average, maximum and minimum acceleration along the y-axis, the speed of change along the z-axis and the orientation were selected [28].

Table II *sleep monitoring overview*

Algorithm characteristics	Content
Aim & Scope	Duration, regularity, deepness, state transition, subjective feeling
Wearable mode	intrusive, unobtrusive
Sensor type	accelerometer, gyroscope, tilt switch, ambient sensor-assisted
Placement	wrist, chest, belly, foot, etc.
Approach	Threshold detection, machine learning

In the study of Ojetola et. al. [38], two sensor motes (each has one accelerometer and one gyroscope) that are wore on chest and right thigh are used to differentiate activities of daily living (ADL) and fall. In the system, raw data is first processed by mean filter and lower re-sampling, then vector magnitude of acceleration and angular velocity are used as features to train a C4.5 decision tree model.

3.3 Sleep Monitoring

Sleep monitoring is a crucial indicator of human health and it intends to provide a measurement of sleep quality. Sleep quality consists of various aspect such as sleep duration, sleep regularity, sleep deepness, personal subjective feeling, etc. With its great effectiveness to the medical and clinical area, many studies that use inertial sensors have been done. We categorize sleep monitoring techniques into three types according to the methods they use. Table II shows a overview of sleep monitoring algorithm. The ground truth is often gained by diary, survey or camera.

1) Activity-based Monitoring:

i. Commercial product introduction: The research of sleep monitoring based on actigraphy [45] (activity-based monitoring technique in medical area) has proved its reliability and validity. Accelerometers strong indicate the activity, and many commercial devices such as Jawbone[2] wristband, Fitbit[21], Xiaomi [4] that embedded accelerometers could monitor sleep have been commercialized and spread to public.

ii. By detecting wrist movement: Koristof [53] uses a energy-efficient wrist-worn device Porcupine [52] that exploits tilt switches and light sensors to detect sleep postures, amount of motion and night segment. Sleep postures include left lateral, supine and right lateral in basic scenario to detect. The paper identifies the night by classifying the light condition by threshold and achieve a high accuracy. A single tilt switch will output binary (0,1) depends on its posture, and 9 tilt switches are placed 45° angles between each other in the system. The research reveals the 9-bit binary string generated by 9 tilt switches correlate with the body posture strongly. The ground-truth is obtained by a modified webcam and the result is on average 80\% for basic posture.

iii. By unobtrusive approach: Besides intrusive devices, unobtrusive devices could be more comfortable for users. Sleep Cycle is an iphone-based application that could sense body movement and determine the sleep stage [20] based on the build-in accelerometer. The application needs user to place the iphone in a proper place on the bed. Enamul et. al. [20] placed several accelerometers on the bed and detect the body movement(left, right, stomach, back, etc.) and sleep phase by training a naive Bayes classifier. Joonas et. al. [40] takes the advantages of a flexible piezo-electric force sensor that is placed between the mattress topper and mattress. In the study, heart rate was modeled by linear latent variable model, and respiration cycle was extracted by a band of low-pass filter [39] if a proper cycle was detected. Finally the sleep information is extracted by heart rate, respiration and activity information.

3) Ambient Sensor-assisted Approach: Only detecting sleep by accelerometer and activity are either intrusive or inaccurate, therefore combining assisting sensors and machine learning techniques to train the data are more intelligent and effective.

Min et. al. [33] build Toss ‘N’ Turn (TNT), which uses seven sensors (accelerometer, microphone, proximity sensor, etc.) on the smartphone. The system uses general statistical features and training a classifiers to distinguish sleep/wake and good/poor sleep state.

Chen et. al. [13] proposed an best effort sleep (BES) model based on smartphone. The BES model takes account of features include light condition F_1, phone usage F_2 ~ F_4(duration of lock phone charging, phone off), stationary F_5 and silence (quiet/noisy) F_6. The BES assumes the sleep duration is linear combination of these features:

$$Sl = \sum_{i=1}^{6} \alpha_i F_i$$

Where $\alpha_i \geq 0$. The ground truth is obtained by the required diary of user, and a regression model is trained:

$$min \sum_{j=1}^{4}(Sl^j - \sum_{i=1}^{6}\alpha_i F_i)$$

The BES has an acceptable sleep duration accuracy only based on smartphone, and is automatic and free the user from any other efforts.

3) Monitoring by Physiology Features: Breathing information is valuable in sleep monitoring algorithm. Many researches employed various features of breathing to detect breathing and sleep information. Krejcar et. al. [26] detect sleep state by detecting the periodical snoring sound from smartphone in a coarse-grained level. Later, Hao et. al. [18] and Ren et. al. [43] use the sound from microphone to detect sleep quality and recognize sleep event(couch, snore, etc.). On the other hand, Radio Signal Strength (RSS) caused by chest movement also have been applied in estimating breathing Patwari et. al. [41][25].

IV. Conclusion

This paper presented an in-deep and thorough review on algorithm aspect of health monitoring methods by wearable inertial sensors. In particular, we at first introduced MEMS-based inertial sensors, including the orientation systems and error characteristics of the inertial measurement unit. Then the related health monitoring algorithms are reviewed and introduced, with a focus on three most popular applications: gait analysis, fall detection and sleep monitoring. The sensor features used in these applications are summarized, and the feature extraction algorithms and information processing algorithms are introduced. By this review, a clear map about health monitoring algorithms by wearable inertial sensors is built, which can guide future study or practical applications.

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