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Inertial Measurement Unit-Based Wearable Computers for Assisted Living Applications

A signal processing perspective

There has been a very rapid growth in wearable computers over the past few years. Assisted living applications leveraging wearable computers will enable a healthier lifestyle and independence in a variety of target populations, including those suffering from neurological disorders, patients in need of rehabilitation after surgical procedures or injury, the elderly, individuals who might be at high risk of emotional stress, and those who are looking for a healthier lifestyle. Application paradigms for assisted living include activities of daily living (ADLs) monitoring, indoor localization, emergency and fall detection, and rehabilitation. All of these applications require monitoring of movements and physical activities for individuals. Wearable inertial measurement unit (IMU)-based sensors can offer low-cost and ubiquitous monitoring solutions for physical activities. Signal processing techniques with a focus on enhancing accuracy, lowering computational complexity, reducing power consumption, and improving the unobtrusiveness of the wearable computers are of interest in this article, which constitutes the first attempt made at reviewing the literature of wearable IMU-based signal processing techniques for assisted living applications. Various signal processing techniques with the aforementioned performance metrics in mind are reviewed here.

Introduction

Cisco predicts the number of wearable devices will increase from 22 million in 2013 to 177 million in 2018 [1]. Many innovative applications are under development for wearable devices. Assisted living is one of the application areas with major potential impact. There are two common approaches to implementing these monitoring systems: using vision or wearable sensors. Vision-based approaches are considered to be invasive to a user's privacy and suffer from line-of-sight issues for cameras. They may not be available everywhere, and signal processing techniques associated with vision sensors are typically computationally intensive, even though they may provide rich information for

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certain applications. Wearable IMU-based sensors, however, can offer low-cost and ubiquitous monitoring solutions. Typical IMUs consist of a three-axis accelerometer that measures dynamic accelerations caused by motion and gravity and a three-axis gyroscope that measures angular velocities about the three axes. Some IMU sensors also include magnetometers that measure the Earth's magnetic field. These sensors are available as long as the user is wearing them. However, wearable sensors face their own challenges, such as reliability issues associated with wearing the sensors improperly. Moreover, users would only wear a few sensors, and, therefore the systems cannot sense the movements of every joint and limb. Power consumption is another challenge related to wearable sensors. Small form factor, long battery life, comfort, and wearability require low power consumption. Efficient signal processing techniques deliver solutions to address these challenges. Signal processing techniques with a focus on enhanced accuracy, lower computational complexity, and reduced power consumption of the wearable computers are of interest. Our survey article constitutes the first attempt at reviewing the literature of wearable IMU-based signal processing techniques for assisted living applications and reviews various signal processing techniques based on the given performance metrics.

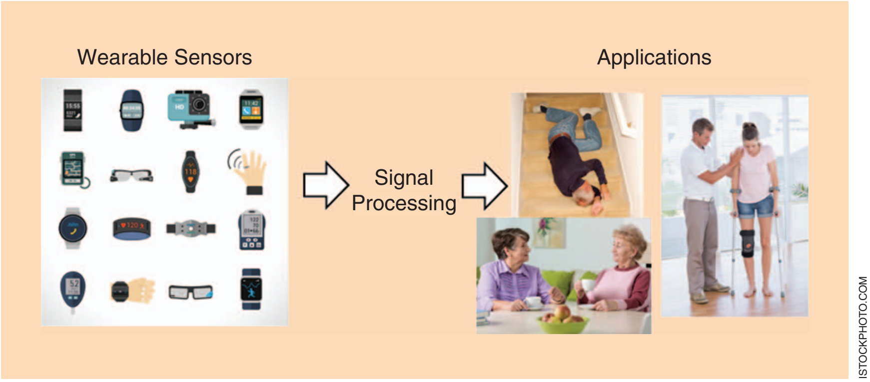

FIGURE 1. Data flow for IMU-based assisted living applications. (Wearable image copyright: Askold Romanov, elderly women copyright: KatarzynaBialasiewicz, fallen man copyright: AnnBaldwin, rehabilitation image copyright: Wavebreakmedia.)

A review of assisted living applications

As mentioned previously, assisted living applications can include ADLs, indoor localization, emergency and fall detection, and rehabilitation. Figure 1 shows the flow for IMU-based assisted living applications and topics. The following are applications that use IMU sensors to make an impact on everyday life.

Activities of daily living

Monitoring and classifying daily activities are keys to assessing the quality of life of various target populations. In this article, the ADLs tracked using IMUs are categorized into postural transitions (e.g., sit-to-stand and stand-to-sit), periodic movements (e.g., walking and running), eating, and sleeping habits. As people get older, performing daily tasks can become challenging. Due to the high cost of health-care centers and the need for the elderly to live independently in their homes, developing IMU-based monitoring systems for ADLs is becoming more important [2], [3]. This is not limited to assisting the aging population, it can also help many others. IMU-based wearables allow workers to function more efficiently and without distractions by providing information based on their current activity [4]. People can track their sleep patterns by wearing an IMU-based sensor on their wrist to detect and log the duration of their sleep/awake time [5]. Users are also able to automatically track their dietary activities by detecting the arm and trunk intake gestures, chewing, and swallowing of food [6]. IMU-based wearables are a part of smart environments that monitor and recognize human gestures so that robots can assist them or the users can control things based on their hand gestures [7], [8]. These types of applications can influence the quality of life for those with disabilities. Several challenges need to be considered for monitoring and classifying ADLs using IMUs. These include sensor displacement, variations in the movements and environments, and the form factor of the sensors.

Indoor localization

People spend a considerable amount of their time indoors, so it can be very useful to have indoor localization systems. Human localization plays an important role in creating context-aware smart environments. IMU-based localization has been used in many applications such as location-aware computing [9], estimating energy expenditure in human walking [10], military operations [11], and finding specific locations in a building [12]. Assisted living technology can greatly benefit from IMU-based indoor localization. Some applications include locating users and providing directions to a desired place in a building and reducing the time necessary for first responders to find people in an emergency situation. It is necessary for such a system to be reliable and report the position accurately. A global positioning system (GPS) is mainly used for outdoor localization; due to obstacles and materials used in the buildings, it may not be available for indoor localization. A local positioning system (LPS) uses modalities such as received signal strength (RSS), vision, ultrasound, and inertial data to provide the location information within a specific coverage area. RSS and ultrasound approaches suffer from signal attenuation, while vision systems have line-of-sight issues. Pedestrian dead reckoning (PDR) is an alternative approach that estimates the user's movement by detecting steps, estimating stride lengths, and the direction of motion based on inertial data collected from body-worn sensors [13].

Emergency and fall detection

Elderly people are prone to falls, which may cause injury. This is a major area of concern in assisted living because these injuries can result in long-term hospitalization and medical costs.

Therefore, a fall detection system is necessary in assisted living. There are two major considerations for this application: 1) speed of detection and 2) accuracy of detection. The first is important because the nature of this application is to prevent injuries caused by falling if possible. For example, having a system that can detect falls before the user hits the ground becomes very promising if the system can activate a protective device (e.g., air bags attached to the user's hip). If no protective device is available, it is critical to get help to the user as soon as possible. The second consideration is necessary to ensure that falling events are properly detected and there are no false or missed detections. Several methods have been proposed using IMU sensors to detect falls before the target hits the ground [14], [15]. In these methodologies, detection speed is very important and challenging. Another approach reliably detects falls while also finding other common human activities that may share similar attributes (e.g., standing to lying in bed) [16]. Many elderly people cannot stand after falling due to injuries sustained, and an emergency message is needed to inform the hospital or care center [8].

Rehabilitation

There are many cases in which clinicians do not need to keep patients in the hospital to observe the recovery process after an operation or treatment. IMU-based systems can play an important role here and can allow patients to live independently in their homes while being monitored remotely by clinicians. The idea behind such systems is to provide general information about the effect of certain behavioral recommendations without having the patient admitted to a rehabilitation center or a laboratory for observation [17]. IMU sensors are able to measure the muscle strength and power by detecting high-frequency body sway [18] and the speed with which muscular forces produce movement of body segments [19]. Estimating knee joint flexion or extension angles can be used to infer activity type or intensity, muscle activity, and gait events [20]. Monitoring ADLs is also a key for evaluating changes in physical and behavioral profiles of the elderly and other patients, including obese people [21]. For example, increasing activity levels after surgery can be used to indicate overall improvement as well as efficacy of therapeutic procedures [22].

Signal processing techniques

Signal processing techniques translate the physical signals sensed from wearable IMU sensors into useful information required by target applications. In this article, our goal is to review the signal processing techniques from various perspectives, including preprocessing, feature extraction, feature selection, classification, and measurement models.

Preprocessing

For IMU-based assisted living applications, the raw sensor data usually gets preprocessed to remove noise from the signal and to determine the segments of interest. These tasks are called *filtering* and *segmentation*. Filtering techniques retain the useful information in a signal while rejecting unwanted information based on the application. Segmentation techniques are used to determine the duration of the movements or events of interest.

Three different types of filters are used: low-pass filters, high-pass filters, and band-pass filters. A low-pass filter is used to remove high-frequency noise for a recognition task of five hand gestures [7] and for physical activity monitoring for assisted living [16]. A 17-Hz low-pass filter is used to reject electronic noise in gyroscope data for sit-to-stand and stand-to-sit measurements [8]. Based on the walking frequency of test subjects, a 3-Hz low-pass filter is applied to remove noise from walking signals [12]. A 6-Hz low-pass filter is applied for balance control measurements during sit-to-stand movements [18], while a low-pass filter with a cut-off frequency of 3 Hz is used to preprocess raw data for sit-to-stand parameter measurement [19]. The accelerometer measurement consists of gravitational acceleration and dynamic acceleration caused by motion. In some applications, only one part of the acceleration is used, and filtering techniques are applied to reject the other one. A 1-Hz low-pass filter is used to remove the dynamic acceleration, and thus the direction of the gravity vector is found during quasi-static activities [15]. A 1-Hz high-pass filter is used to reject the gravitational acceleration, which, in turn, removes the effect of the gross changes in the orientation of the body segment where the sensor is placed [23]. Some applications may only look at signals within a certain frequency range, and the band-pass filter can be used to preprocess the data. A 3–11-Hz band-pass filter is used to clean the accelerometer signal for detecting sleep and awakening phases [5]. For motor fluctuation monitoring in Parkinson's disease patients, a 3–8-Hz band-pass filter is used for the analysis of tremors, and a 1–3-Hz filter is applied for analysis of bradykinesia and dyskinesia [23]. The sliding window segmentation technique is simple and effective and is often used in the reviewed literature for segmentation [6], [7], [14], [17], [24], [25].

Feature extraction

Features are normally extracted from the sensor data depending on their effectiveness in a particular application. Feature extraction starts with the preprocessed sensor data and generates derived values that are intended to be informative and nonredundant while enabling subsequent learning and generalizing the data, which will lead to better human interpretation. The features are divided here into four categories: time domain features, frequency domain features, time–frequency domain features, and others. The time domain features are the general statistical measurements that can represent the generalization of the data. The frequency domain features analyze the frequency performance of the sensor signals, which is usually the periodicity of the signal over a long duration (i.e., periodicity of the walking). The time–frequency domain features refer to features that contain both time and frequency information simultaneously with different time–frequency representations (e.g., short-time Fourier transform, wavelets) that are useful for nonstationary signals (e.g., postural transitions). The other features refer to the features that have specific meanings to specific applications (e.g., posture transition duration for fall detection and step length for gait analysis). Table 1 lists commonly used features of IMU sensors in assisted living applications.

The time domain features listed in Table 1 are primarily the general statistical features of a signal. Among those, signal vector magnitude and root mean square (RMS) look at the magnitude of the three-axis signal and do not contain directional information from the IMU sensor. These features usually play an essential role in movement classification and detection tasks if the most discriminative feature is not known. The frequency domain features are good at analyzing stationary signals that contain certain frequency patterns. For example, the fast Fourier transform (FFT) features for a certain long duration can be used to distinguish between walking, falling, and sitting down activities [2] and to distinguish between walking, running, standing, and going up stairs [27]. The principal frequency component can be considered to monitor the motor fluctuation of patients with Parkinson's disease [23]. The time–frequency domain feature listed captures the frequency features as well as the time at which the frequency component occurs. This information is important for analyzing nonstationary signals in which the frequency components change over time. This is true for all the transitional movements (e.g., sit-to-stand and sit-to-lie). This feature has been proven powerful for detecting daily activities of elderly subjects, which primarily consist of transitional movements [22]. It is also used to detect the postural transition time, which helps evaluate the fall risk of the elderly [8]. A comparison work shows that frequency domain features (FFT-based features) perform better than wavelet transform features in distinguishing continuously dynamic activities such as walking, walking upstairs, walking downstairs, running, and jogging [26].

The first three categories in the table generalize the signal based on statistics. The fourth category includes the features that are useful for certain applications. To extract these features, users are required to be knowledgeable about the application so that they know which features will best serve their purpose. Posture transition duration [3], [18], trunk tilt [3], and vertical velocity [15], [28] are among the features that can be used to detect and evaluate the sit-to-stand motion. Step and stride length, velocity, cadence, swing, and stance are important in gait analysis [21]. Step length and heading are commonly used features for indoor localization [9], [11], [13].

Feature selection

In the previous section, we covered the extraction of various features from the IMU sensor data. Feature selection provides a way to select the most suitable feature subset for certain tasks from the available features. For example, to reduce over fitting and information redundancy, feature selection techniques can be applied to select the best feature subset for classification and detection tasks. It is useful when users do not know which features are useful and want to pick the best subset from a broad of set of existing features. Here, feature selection also refers to the investigation that analyzes the sensitivity of different features for applications.

There are three different methods of feature selection: wrapper, filter, and embedded. Wrapper methods use a predictive model to score feature subsets. Each new subset is used to train a model that will be tested on the rest of the data set. Based on the prediction performance, each subset is assigned a score and the best subset will be chosen. Filter methods use general measurement metrics of a data set to score a feature subset instead of using the error rate of a predictive model. Some common measures are mutual information and inter/intra class distance. The embedded methods perform the feature subset selection in conjunction with the model construction. One example is the recursive feature elimination algorithm, which is commonly used with a support vector machine (SVM) to repeatedly construct a model and remove the features with low weights. The different feature selection techniques are stated next for assisted living applications.

A large set of features are extracted and a wrapper-based feature selection technique is applied to determine the best subset of the feature space in a preimpact fall detection application [14]. Each individual feature is assigned a ranking score based on its discriminative performance, and the best ranked features are selected to form a final feature vector and fit it to the classification algorithm. A framework is proposed to determine the best sensor locations and the most relevant sensor features for discriminating ADLs that can be important to assess physical and behavioral changes over time for the

Table 1. A list of features.

Feature Category	Feature List
Time domain	Mean, variance, signal vector magnitude, correlation coefficient, RMS, skewness, maximum magnitude change, slope of the fitting line, standard deviation of fitting error, standard deviation of difference, trapezoidal numerical integration, signal entropy, maximal acceleration, maximal jerk, maximal velocity, peak power, range of cross covariance between each of two axes [2], [3], [14], [16], [19], [22], [23], [26]
Frequency domain	FFT coefficients, principal frequency components, energy of 0.2-Hz window centered on the main frequency over the total FFT energy, logarithm of the magnitude-squared discrete Fourier transform coefficients [2], [23], [26], [27]
Time–frequency domain	Wavelet transform [8], [22]
Others	Posture transition duration, trunk tilt, vertical velocity, step length, step frequency, heading information, local energy of the trunk dynamics, postural transition smoothness, postural orientation, singular value decomposition, cadence, swing, stance [3], [9], [11], [12], [15], [16], [18], [21], [28]

elderly and patients with chronic diseases [24]. Three different feature selection algorithms are tested for 13 different features for five different groups of ADLs. Accelerometer based balance parameters are determined and compared during the sit-to-stand movement and the results show the area under the curve (AUC) and RMS are useful features and AUC appeared to be more sensitive than RMS [18].

Classification

Classification is widely used in applications of assisted living. Classification can be used to detect falls and prefalls, to distinguish between healthy and unhealthy motor function, and to detect ADLs. A variety of machine-learning and pattern recognition algorithms are explored in the area of the IMU-based assisted living. Table 2 shows some of the commonly used classification algorithms.

Thresholding-based decision making is a popular classification scheme in assisted living applications. This approach is straightforward to use and is often used for binary classification tasks. When the value of a feature is above a threshold, it is classified as one of the two states and when the value is below a threshold, it is recognized as the other. When the designer finds a feature that can discriminate between two possible states, the thresholding technique is a good candidate due to its simplicity and because it can be easily interpreted. The thresholding technique is applied to classify walking versus running [10]. If the variance of the accelerometer is below a defined threshold, the activity is recognized as walking, and recognized as running if the accelerometer variance is larger than a defined threshold. Based on this decision, an adaptive step length estimation algorithm is derived. A thresholding technique is applied to the inertial frame's vertical velocity magnitude to detect the occurrence of falls before impact [28]. To determine the posture transition time for sit-to-stand, a threshold is applied to determine the beginning and ending of the transition movement [8]. A threshold based on the maximum measured vertical velocity from ADLs and the minimum measured vertical velocity from falls is used to distinguish falls and normal activities [15]. Thresholding is used to distinguish tremor motions from nontremor motions in a movement from the action research arm test, which is designed to test recovery of upper-limb function [29].

Feature selection provides a way to select the most suitable feature subset for certain tasks from the available features.

Instance-based learning methods classify an instance based on the similarity between the instance under test, and the labeled instances in the training data set. This method does not need to train a model in the training phase. However, it is computationally expensive in the testing phase because it needs to calculate the similarity between each testing instance and all of the instances in the training set. The *k*-nearest neighbors (kNN) algorithm is one example of an instance-based classification algorithm. It performs well in activity recognition tasks, and it is used to determine the different types of the ADLs [16], [24].

Neural networks are a family of statistical algorithms inspired by biological neural networks (i.e., the human brain). It consists of a large number of nodes acting as neurons in a network and the weighted connections between different neurons. With a large enough set of training data and parameter tuning, it can provide high classification performance. A very large data set is often required for training, and this is not usually available for IMU-based applications. Moreover, the trained model is not interpretable for users. In IMU-based assisted living applications, the training data is usually small, and, in most cases, the user wants to understand the models. These two factors make neural networks less attractive in this area. The authors explored the classification performance of a neural network while varying the size of the training data set for a physical movement monitoring application [16]. Four transition movements were detected using the neural networks and kNN for an average accuracy of 84%.

SVM is one of the most popular discriminative classification algorithms in different areas in recent years. SVM tries to find the margins that will maximize the separation between different classes. In the training phase, the margins are determined and it is computationally efficient in the testing phase based on the trained model. It is similar to neural networks in that it will be difficult to interpret by users. However, it does not require a very thorough training or a very large training data set. A preimpact fall detection system is discussed based on the SVM classifier [14]. A SVM is applied for monitoring motor fluctuations in patients with Parkinson's disease and the optimal kernel is analyzed [23].

The HMM is a statistical Markov model in which the system is assumed to be a Markov process with unobserved states. HMM is well studied and is often used in temporal pattern recognition such as speech recognition and gesture recognition. It is widely used to recognize different activities based on IMU time series sensor data and is also good at recognizing a sequence of movements. Human intention recognition in smart assisted living systems is presented using a hierarchical HMM [7]. The HMM is first used to recognize the low-level hand gestures with a finger-worn inertial sensor

Table 2. Classification algorithms.

Classification Type	Classifier
Thresholding	[6], [8], [10], [15], [28], [29]
Instance based	KNN [16], [24]
Neural networks	Multilayer perceptron [16]
SVM	Linear kernel SVM [14], polynomial kernel SVM [23]
Hidden Markov models (HMMs)	Hierarchical HMM [7], continuous HMM [27], HMM [4], [17]

and, after that, a hierarchical HMM is applied to model the correlation and constraints between commands. A continuous HMM is proposed to jointly classify the pedestrian activity and gait phases with the assumption that state-conditional output density functions of the HMM to be a Gaussian mixture model [27]. This approach is robust to subject variability. It will still perform well when new subject data is tested without any training for this subject. In-home assembly task recognition is performed using a HMM on accelerometer data with fusion of the linear discriminant analysis (LDA) decision from sound data [4]. A method for spotting sporadically occurring gestures (e.g., handshake, drink, pick up the phone, etc.) in a continuous data stream from body-worn inertial sensors was designed using a HMM [17]. The method contains two stages. In the first stage, signal sections likely to contain specific motion events are selected using a similarity searching algorithm; and in the second stage, the HMM is applied to classify the activities.

Measurement models

In addition to classification algorithms, advanced measurement models are applied to fuse different modalities of IMU sensors (e.g., accelerometer, gyroscope, and magnetometer) to compensate for errors and drifts. This leads to robust measurements for different tasks in assisted living. Kalman filters and particle filters are among the most popular fusion techniques. The Kalman filter is an algorithm that uses a model and a series of noisy and possibly inaccurate measurements observed over time to produce estimates of unknown variables that tend to be more precise than those based on a single measurement alone. It is widely used in the navigation and control systems. A conventional Kalman filter is used to reduce the drift from inertial sensors in an indoor navigation system with foot-mounted strap-down inertial sensors [11]. The inertial navigation system calculates the position change at a high frequency rate, and the integration error from the inertial sensor will accumulate over time. The GPS is also a part of the system and when GPS data is available, the GPS derived positions are compared with the positions derived from the inertial navigation system. The differences are fed into a Kalman filter that estimates the errors from the inertial navigation system and compensates the measurements so that the errors remain small. A Kalman filter is used to combine the acceleration, angular velocity and biomechanical constraints to generate robust estimation of the knee joint flexion/extension angles [20]. The gyroscope noise and the accelerometer noise are modeled by the Kalman filter. The proposed system works effectively for both walking and running for five minutes when compared to a camera-based motion tracking system.

Unlike the Kalman filter, the adaptive filter is a system with a linear filter that has a transfer function controlled by variable parameters that are adaptively updated according to certain optimization criterion. An adaptive filter is designed to fuse all of the sensor information and pseudo-measurements to provide a self-contained pedestrian tracking system during normal walking [9]. In the cases that the systems are nonlinear and the noise is non-Gaussian, a particle filter, which is more complex, will usually perform better than a Kalman filter. A particle filter is used to fuse the step length and heading information from inertial sensors to provide an indoor localization system [12].

Classification can be used to detect falls and prefalls, to distinguish between healthy and unhealthy motor function, and to detect ADLs.

Performance analysis

The performance and efficiency of assisted living technologies can be evaluated using many metrics. The goal for this section is to compare recent signal processing advances with respect to accuracy, power consumption, and computational complexity of the sensors and algorithms.

Accuracy

The accuracy of IMU-based signal processing techniques is a key aspect for assisted living applications. The cost of faults can be significant, especially when the techniques are used to assist the elderly, individuals who are vulnerable, and those that are in need of care.

Signal processing techniques are proposed to reliably detect the human postural transition and ADLs, recognize gestures, and track the users' sleeping patterns and diet. FFT was used to extract information from IMU sensor data to recognize and distinguish falling, sitting, and walking activities [2]. Using FFT on data from a wrist-worn sensor with a 10-Hz sampling rate was unable to accurately discern between falling and sitting down. A method of physical activity monitoring to detect activities such as sitting, standing, and lying has sensitivities and specificities of 90.2% and 93.4% for sitting, 92.2% and 92.1% for standing+walking, and, 98.4% and 99.7% for lying with a sternum-mounted sensor sampling at 40 Hz [22]. Overall, the detection errors were 3.9% for standing + walking, 4.1% for sitting, and 0.3% for lying. Finally, the overall symmetric mean average errors were 12% for standing + walking 8.2% for sitting, and 1.3% for lying. A model to fuse data from hand movements and audio sampled at 2 kHz from a wood workshop to recognize workers' activities is presented [4]. Different methods were used to improve the classification and it is shown that in isolation, the accuracy of activity detection is 98%, 87%, and 95% for the user-dependent, user-independent, and user-adapted detection, respectively. A data set was created from a wrist-worn IMU sensor, and a method to detect sleep and wake states was proposed [5]. The algorithm was compared with traditional algorithms using total sleep time (TST) and sleep efficiency (SE) as the comparison parameter. The proposed method achieves an overall median accuracy of 79% for detecting sleep and wake intervals.

Several accurate human localization techniques are proposed, leveraging IMU-based wearable solutions. An adaptive step-length estimation algorithm for the pedestrian navigation system (PNS) has an accuracy of 95% in the worst case [10]. Two PDF algorithms including Weiberg and zero velocity updates (ZVU) for stride-length estimation are tested at three different walking speeds (slow, normal, and fast) [13]. The authors show that the Weiberg algorithm performs better than ZVU at all walking speeds. An IMU-based self-contained pedestrian tracking method is proposed that uses ZVU and the step length estimation as a control variable to correct the acceleration drift. This method improves the tracking accuracy by decreasing the final position error for different scenarios such as short and long distance walking and reduces the final position error up to 66% when compared to other algorithms [9]. A method using IMU sensors attached on soldiers' boots is compared to the implementation of ZVU with and without magnetic heading information [11]. Using ZVUs along with magnetic heading information can be accurate for the soldiers when they are operating an attack in a building. This method stayed within 2 m of the true path over a path of more than 90 m. A method using phone inertial sensors with a default rate of 50 Hz is proposed, i.e., infrastructure-free, phone position independent, user adaptive, and easy to deploy [12]. The step-length estimation is used as a personal model for a user and this model is updated each time the system collects data. The users are put into different groups based on their personal models. The step-detection error for the cellphone in hand and in pocket cases for different algorithms were compared and error rates from 1.6% to 24.5% (in hand) and 1.1% to 25.6% (in pocket) were reported. An investigation using IMU sensors sampling at 1 kHz detects preimpact falls using trunk vertical velocity [15]. Falls can be distinguished from normal ADLs, with 100% accuracy and with an average detection speed of 323 millesconds prior to trunk impact and 140 milliseconds prior to knee impact, in their subject group. Sensor locations and sampling can impact accuracy. This information for the reviewed papers is given in Table 3.

Table 3. Sensor sampling rate and location.

Sensor Sampling Rates		Sensor Locations	
100 Hz	[4]–[6], [9]–[11], [13], [17], [20], [23]	Wrist/Hand	[2], [4]–[7], [12], [17], [23], [24], [26], [29]
50 Hz	[7], [12], [19], [24], [29]	Hip/Waist	[14], [19], [24], [25], [28]
40 Hz	[3], [8], [22]	Thigh	[14], [20], [21], [23], [26]
Below 40 Hz	10 Hz [2], 25 Hz [25], 32Hz [21]	Sternum/ Trunk	[3], [7], [8], [15], [16], [18], [21], [22], [24], [27]
47 Hz	[14]	Lower Leg/ Calf	[20], [23]
57 Hz	[28]	Ankle/Foot	[7], [9]–[11], [13], [21], [25], [26]
64 Hz	[26]	Upper Arm	[4], [6], [17], [24], [29]
Above 100 Hz	128 Hz [18], 250 Hz [27], 1 kHz [15]	Other	Ear [24], pocket [12], knees [25]

Power consumption/computational complexity

Power-aware IMU-based sensors can potentially reduce the size of batteries, enhance sensor lifetime, and enable long-term monitoring. Signal processing algorithms with lower computational complexity make it possible to analyze the collected data more quickly and provide faster feedback. Exploring the lowest sampling rate for activity detection using FFT features can save power [2]. The results show that 10 Hz is able to distinguish between walking and sitting, but does not do well distinguishing falling with a wrist-worn accelerometer. A granular decision-making module is proposed to reduce the power consumption significantly for a wearable IMU-based movement monitoring system [30]. Movements that are of no interest are removed as early as possible from the signal processing chain, deactivating all of the remaining modules in the signal processing chain as well as the microprocessor. The bit resolution, the key factor that affects the system power consumption, is only increased as the target movement is detected. Similarly, a low-power programmable signal processing architecture for dynamic and periodic activity monitoring applications saves power by performing signal processing in a tiered fashion by removing irrelevant data as soon as possible [25]. Using wavelet decomposition 75.7% power savings are achieved while maintaining 96.9% sensitivity detection of target actions.

Conclusions

The growth of wearable IMU sensors has created many opportunities to improve people's health and lives through the development of innovative applications. This article has provided an overview of signal processing techniques and their performance for assisted living applications. Many of the applications reviewed are the subject of ongoing research and there many opportunities for improvement still remain. A variety of signal processing techniques are being used, but for an actual working system, the accuracy and power concerns must be taken into consideration on a case by case basis noting that applications and related hardware have different needs. Applications using wearable IMU sensors will continue to improve and provide valuable information to help people to have healthier lifestyles with greater independence.

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