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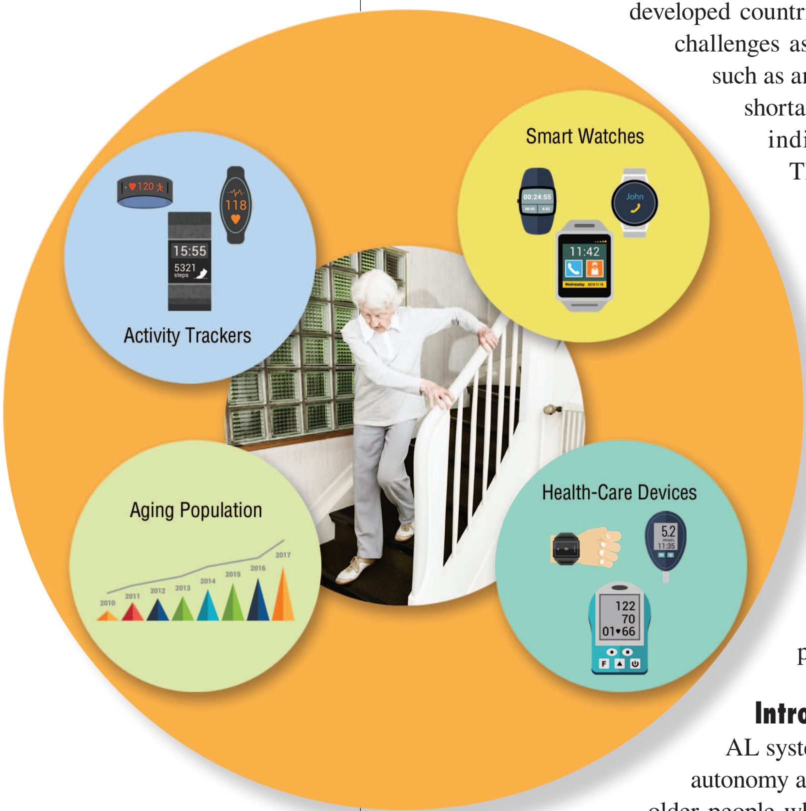
Sensors in Assisted Living

A survey of signal and image processing methods



Our society will face a notable demographic shift in the near future. According to a United Nations report, the ratio of the elderly population (aged 60 years or older) to the overall population increased from 9.2% in 1990 to 11.7% in 2013 and is expected to reach 21.1% by 2050 [1]. According to the same report, 40% of older people live independently in their own homes. This ratio is about 75% in the developed countries. These facts will result in many societal challenges as well as changes in the health-care system, such as an increase in diseases and health-care costs, a shortage of caregivers, and a rise in the number of individuals unable to live independently [2]. Thus, it is imperative to develop ambient intelligence-based assisted living (AL) tools that help elderly people live independently in their homes. The recent developments in sensor technology and decreasing sensor costs have made the deployment of various sensors in various combinations viable, including static setups as well as wearable sensors. This article presents a survey that concentrates on the signal processing methods employed with different types of sensors. The types of sensors covered are pyro-electric infrared (PIR) and vibration sensors, accelerometers, cameras, depth sensors, and microphones.

Introduction

AL systems basically aim to provide more safety and autonomy and improve wellness and health conditions of older people while allowing them to live independently, as well as relieving the workload of caregivers and health providers.

A fundamental component of the AL systems is the use of different types of sensors to monitor the activities of the residents. These sensors can be broadly categorized into two groups: 1) static sensors at fixed locations, e.g., PIR sensors, vibration sensors, pressure sensors, cameras, and microphones, and 2) mobile and wearable sensors, e.g., accelerometers, thermal sensors, and pulse oximeters. There are several choices of specific sensors or sensor combinations—currently there are many AL

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systems implementing various tasks, such as fall detection [3]–[5], mobile emergency response [6], video surveillance [7], automation [8], monitoring activities of daily living [9], and respiratory monitoring [10]. Falls among the elderly are a major concern for both families and medical professionals. Falls are considered to be the eighth leading cause of death in the United States [11] and fall injuries can result in serious complications [12], [13]. Autonomous fall detection systems for AL can reduce the severity of falls by informing other people to deliver help and reduce the amount of time people remain on the floor. These systems can increase safety and independence of the elderly.

To truly assist elderly people, an AL system should satisfy some basic requirements [14]:

- *Low-cost:* Almost 90% of the older adults prefer to stay in the comfort of their own homes. Therefore, an AL system should be affordable by the average elderly person or couple.
- *High accuracy*: Since the aim is to enhance the wellness and the life quality of elderly people, a tolerable error rate should be achieved.
- *User acceptance*: The AL systems should be compatible with the ordinary activities of people so that they can interact with the system easily, i.e., by speaking naturally, using simple gestures, etc. Also, users do not find wearable systems or those that need to be carried practical. Thus, contact-free and remotely controllable systems are desired.
- *Privacy*: The AL systems should be nonvisual and share minimal private data with the monitoring call center regarding the daily living activities of individuals.

The most important signal processing problem in AL systems is the recognition of human activity from signals generated by various sensors including vibration sensors, PIR sensors, and wearable accelerometers.

Despite the presence of surveys [2], [15], [16] and proliferation of different types of sensors in the AL field, a comprehensive study concentrating on the utilized sensor signal processing methods is not available. This article aims to provide an overview of most recent research trends in the AL field by focusing on PIR sensors, vibration sensors, accelerometers, cameras, depth sensors, and microphones and the related signal processing methods, which together meet most of the aforementioned requirements. Ambient information monitoring sensors are used in home safety [17]–[19], home automation [8], [20]–[23], activity monitoring [14], [24]–[27], fall detection [28]–[34], localization and tracking [35]–[37], and monitoring the health status indicators of elderly and chronically diseased people outside hospitals [38]–[44].

Human activity recognition using various sensor modalities

The most important signal processing problem in AL systems is the recognition of human activity from signals generated by various sensors including vibration sensors, PIR sensors, and wearable accelerometers. Obviously, each sensor generates different kinds of time-series data. Therefore, signal-processing and machine-learning algorithms tailored for each specific sensor need to be developed.

PIR sensor signal processing

PIR sensors are low-cost devices designed to detect the presence of moving bodies from stationary objects. They are easy to use and can even work in the dark, unlike ordinary vision-based systems, because they image infrared light. A PIR sensor functions by measuring the difference in infrared radiation between the two pyro-electric elements inside of it. This difference occurs due to the motion of bodies in the viewing range of the sensor. When the two pyro-electric elements are subject to the same infrared radiation level, they generate a zero-output signal by canceling each other out. Therefore, the analog circuitry of a PIR sensor can reject false detections very accurately.

PIR sensors are widely used in the context of AL. In [38], eight PIR sensors are installed in the ceiling of hospital rooms to assess the daily activities of elderly patients. The activities are classified in 24 different categories by checking the number of sensors activated and recording the time interval for which they remain activated. Barger et al. [24] introduce a system of distributed PIR sensors to monitor a person's in-home activity. The activity level of the person is defined as the number of sensor firings in a room per time spent in the room. Mixture models are applied to the sensor data in the training set to develop a probabilistic model of event types. These models are then used to identify the type of event associated with each observation in the test set. In [27], a PIR sensor installed in a corner of a living room is employed to detect the abnormalities in daily activities of an elderly person. The PIR sensor sends the value "1" to the controller if there are activities from the person and the value "0" otherwise. Hidden Markov models (MMs), forward algorithms, and Viterbi algorithms are used to analyze the obtained data sequence. If a certain deviation from the constituted models is detected, the caregiver receives an alert. In [26] a wireless sensor network including PIR, chair, bed, toilet, and couch sensors is suggested to determine the wellness of the elderly. Time-stamped sensor activities are recorded and fed to predefined wellness functions.

In [25], PIR and contact sensors are used to assess neurologic function in cognitively impaired elders. The contact sensor is responsible for tracking the presence or the absence of the resident and recording the time spent in the home and out of the home. PIR sensors are utilized for the estimation of walking speed and daily activity. The walking speed of the resident is estimated from the time of PIR sensor firings that are placed sequentially along a hall. The amount of daily activity is decided based on the number of sensor firings per minute when the subject is in the home.

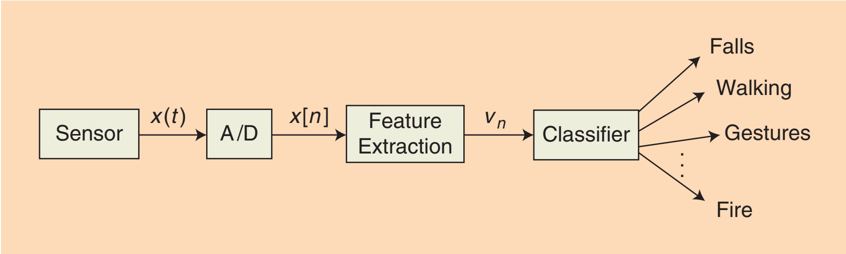


FIGURE 1. A block diagram of an intelligent PIR sensor signal processing system.

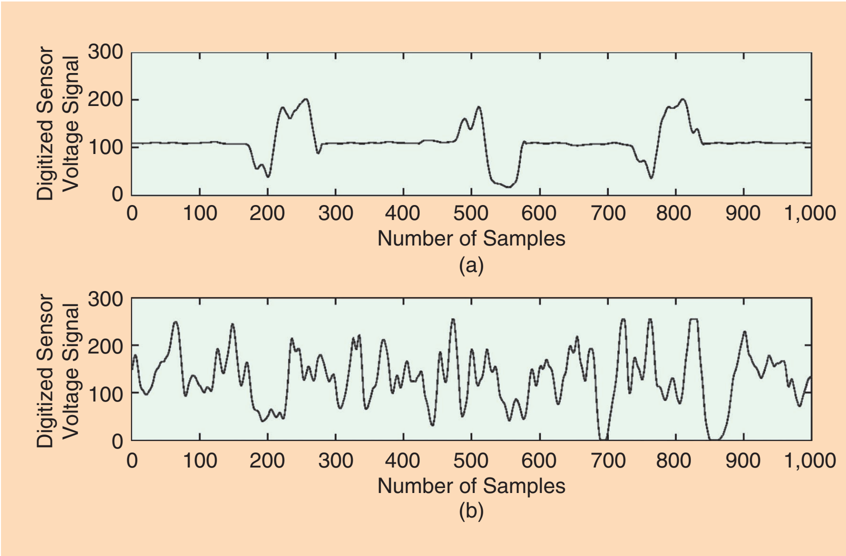


FIGURE 2. A PIR sensor raw output signal recorded at a distance of 5 m (a) for a person walking and (b) for a flame of an uncontrolled fire.

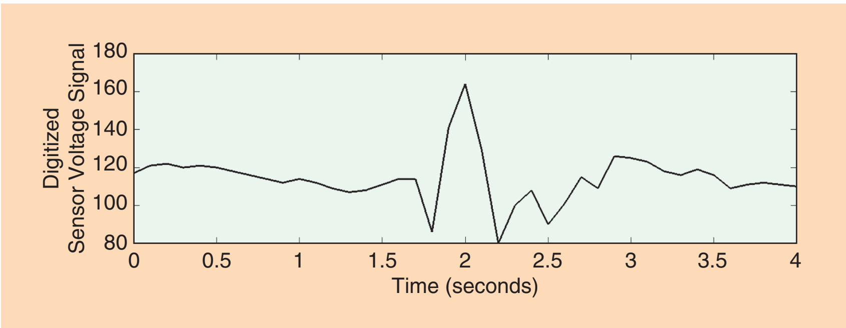


FIGURE 3. A time-domain PIR sensor signal record due to a person falling.

The aforementioned studies all use the binary outputs produced by the analog PIR motion detector circuits. However, it is possible to capture a continuous-time analog signal corresponding to the amplitude of the voltage signal of the PIR sensor that represents the transient behavior of the sensor circuit. By processing these analog signals, more complicated tasks, as opposed to just the on/off type operations, can be accomplished. The block diagram of an intelligent PIR sensor signal processing system is shown in Figure 1. The original output of the sensor signal $x(t)$ is first digitized using an analog-to-digital converter. Feature vectors v_n are then extracted from the digitized signal $x[n]$. It is possible to extract a feature vector for each signal sample. However, it is computationally more efficient to extract a feature vector for a frame of data, as in speech processing systems. Finally, these feature vectors are fed to a classifier to detect the events of interest such as walking, falls, uncontrolled fires etc. The classifier is usually trained using past and/or simulated data.

A PIR sensor-based system for human activity detection is described in [19], [33], and [45]. The system is capable of detecting accidental falls and the flames of a fire. Instead of the binary signal produced by the comparator structure in the PIR sensor circuit, an analog output signal is captured and transferred to a digital signal processor for further processing. As shown in Figure 2(a), a walking event is almost periodic when the person walks across the viewing range of the sensor. On the other hand, a person falling produces a clearly distinct signature as shown in Figure 3, and uncontrolled flames lead to a signal with high-frequency content. Since flames of an uncontrolled fire flicker up to a frequency of 13 Hz, a sampling frequency of 50 Hz, which is well above the Nyquist rate, is chosen. The goal is to recognize falls, uncontrolled fire events, and a person's daily activities. In practice, PIR signals are not as clearly distinguishable as the ones shown in Figures 2 and 3. For example, the person may walk toward the sensor and the periodic behavior is no longer clearly visible.

Wavelet transform is used for feature extraction from the PIR sensor signal. In the training stage, wavelet coefficients corresponding to each event class signals are computed and concatenated. Three, three-state MMs are designed to recognize the three classes. The characteristics of the

In [35], a system to actively assist in the resident's life such as housework, rest, sleep, etc. is described. The system is formed by an array of PIR sensors and locates a resident with a reasonable accuracy by combining the overlapping detection areas of adjacent sensors. In [17], an intruder detection system based on PIR sensors is developed. Mrazovac et al. [8] use a microphone array and a three-dimensional (3-D) camera in addition to PIR sensors for home automation, i.e., to detect the presence of and localize the users for smart audio/video playback control.

transitions between the three states of the MMs are different for each event class. The wavelet coefficient sequence corresponding to the current time window of two seconds is fed to the three MMs, and the MM producing the highest frequency determines the activity within the window. Uncontrolled flames are very accurately detected, since the sensor signal for a flickering flame exhibit high frequency activity that no person can produce by moving his or her body as shown in Figure 2(b).

It is not possible to distinguish a fall from sitting on the floor or a couch using only a single PIR sensor. In [33] and [45], multisensor systems are developed for fall detection. Sound, PIR, and vibration sensors are placed in a home. MMs are used as classifiers in these multisensor systems. They are trained for regular activities and falls of an elderly person using PIR, sound, and vibration sensor signals. Vibration and sound sensor data processing will be described in the next two sections. Decision results of MMs are fused by using a logical "and" operator to reach a final decision.

In [21], a remote control system is developed based on a PIR sensor array and a camera for home automation. The system recognizes hand gestures. The camera is responsible to detect the hands of the user. Once a hand is detected, simple hand gestures such as left-to-right, right-to-left, and clockwise and counterclockwise hand movements are recognized by the PIR sensor signal analysis to remotely interact with an electrical device. The system includes three PIR sensors, each of which is located at a corner of a triangle. Signals received from each PIR sensor are transformed into wavelet domain and then concatenated according to a predefined order. In this case, the distinctive property of the resulting wavelet features for different hand gestures is not the oscillation characteristics, but the order of the appearances of the peaks in the wavelet sequence. Therefore, the winner-take-all (WTA) hashing, which is an ordinal measure, is used for further feature extraction and classification instead of MMs. Wavelet sequences are converted to binary codes using the WTA hash method, and Jaccard distances are calculated between the trained and test binary codes. The model yielding the smallest distance is determined as the class of the current test signal. The system described in [21] produces higher recognition results than the system in [22], which uses only the binary outputs of the analog PIR sensor circuitry for the same task.

In [41], a method for the detection of breathing movement using PIR sensors is proposed. PIR sensors are placed near a person's bed. Sensor signals, corresponding to body movements due to breathing activity, are recorded. Short-time Fourier analysis of the PIR sensors' signals is carried out. The recorded signals are divided into windows, and the existence of sleep apnea within each window is detected by analyzing the spectrum. If there are no peaks in a window, that is an indicator of a sleep apnea. It may also be possible to measure the respiratory rate of a person who is sleeping using PIR sensor signals.

Even though several user-activated commercial devices are available for fall detection, they have limited benefits, especially in situations where the user loses consciousness.

Vibration and acoustic sensor signal processing

Accelerometers designed to measure vibration are either based on the piezoelectric effect or electromechanical energy conversion. They are transducers for measuring the dynamic acceleration of a physical device. All of the commercially available wearable fall detection systems are based on accelerometers. They convert vibrations into electrical signals depending on the intensity of the vibration waves in the axis of the vibration sensor. Vibration sensors can be categorized into two groups based on the number of their axes: one-axis and three-axes sensor types.

As mentioned previously, vibration sensors can be wearable or they can be installed on intelligent homes with the aim of sensing the vibrations on the floor. In this section, we first review the stationary systems.

Regular daily activities, such as walking, running, sitting on a chair, or objects falling on the floor cause measurable vibrations on the floor. Human falls also cause vibrations, which are transmitted through the floor. Therefore, a vibration sensor installed in each room of a house or an apartment can pick up the vibrations on the floor, and it may be possible to detect a human's fall by continuously analyzing the sensor signal. In Figure 4, a ten-second-long vibration sensor signal generated by a person walking is shown. It is clearly different from the human fall signal shown in Figure 5. This signal was recorded on a concrete floor and the fall took place 3 m away from the sensor. Human falls usually take about two seconds and create strong vibration signals because a typical human is more than 100 lb heavier than most of the objects that can fall on the floor in a house. Machine-learning techniques can be used to classify the vibration signals.

In [33], a multisensor AL system consisting of PIR sensors and vibration sensors is developed. Vibration sensor signals are sampled with a rate of 500 Hz. As shown in Figure 5, there is very little signal energy above 125 Hz on a concrete floor. Since vibrations and acoustic and sound waves are related to each other, it is natural to use the feature extraction techniques utilized in speech processing to analyze the vibration signals. Various wavelet and frequency domain feature extraction schemes are employed every two seconds to extract feature vectors from the signals. Wavelet and different frequency analysis methods are studied and compared to each other. Discrete Fourier transform (DFT) subband energy values, MFCCs, discrete wavelet transform (DWT), and dual-tree complex wavelet transform (DT-CWT)-based feature extraction methods are studied for feature extraction [33]. These feature vectors are classified using a support vector machine (SVM) for fall detection. They can also be used to estimate a person's daily activity and can provide feedback to him or her.

In [33], the data set contains 2,048-sample-long signals corresponding to 100 falls, 1,419 walking/running incidents, 30 sitting cases on the floor, 30 slammed door cases, and 65 cases of

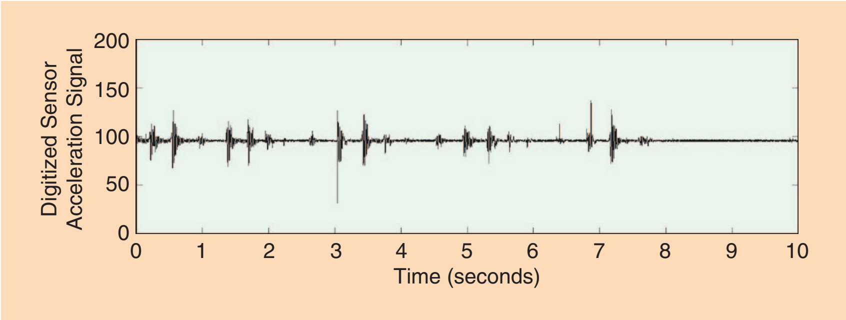


FIGURE 4. A ten-second-long vibration sensor signal generated by a person walking.

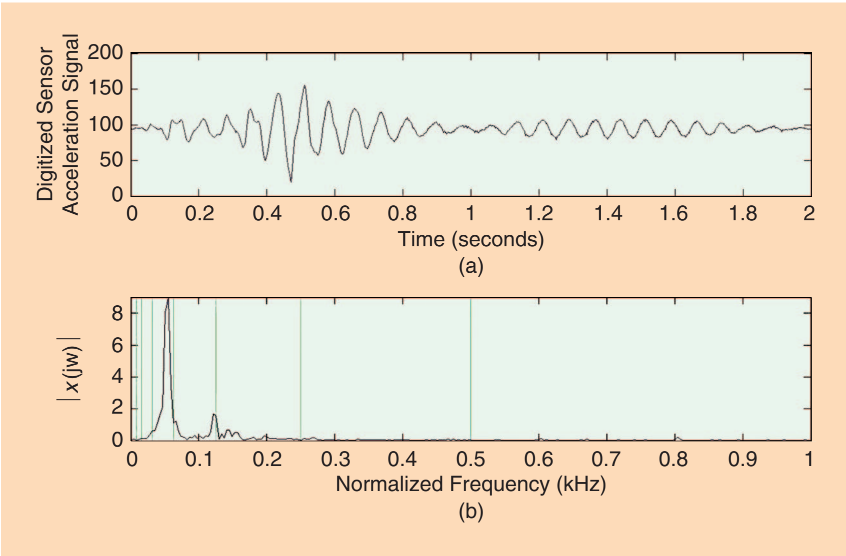


FIGURE 5. (a) A two-second-long human fall record. (b) The Fourier transform magnitude. The Fourier transform domain is divided into eight nonuniform bands, and subband energy values are used as a feature set representing the time-domain vibration signal together with wavelet coefficients and Mel-frequency cepstral coefficiencts (MFCCs).

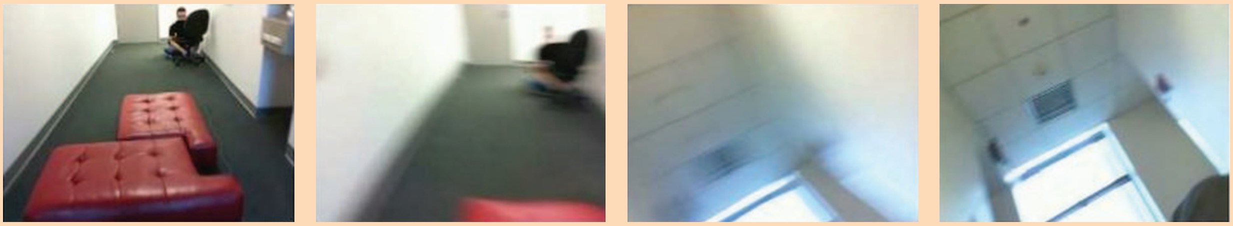
fallen items. Eight MFCCs, eight DFT coefficients, eight wavelet coefficients, and eight CWT coefficients are extracted for each record. About 40% of falling and walking/running records are used for training the SVM classifier. About one-third of sitting, slammed door, and fallen object records are also used for training. Remaining records are used as the test data set. The data set is available to the public. Best recognition results are obtained when complex wavelet transform based features and modified mel-frequency cepstrum coefficients are used. When combined with PIR sensors the multisensor AL system becomes very reliable. The AL system has the capability to place a phone call to a call center whenever a fall is detected.

AL systems may provide safety and autonomy for elderly people while allowing them to live independently, as well as relieve the workload of caregivers and health providers.

In [46], acoustic sensors are used instead of vibration sensors for fall detection. The acoustic sensor is placed like a stethoscope on the floor. In a practical system, it is desirable to have a single vibration sensor unit installed on each floor of a house; however, there are some challenges. This unit has to be robust against variations on the type of the floor and the weight of the person as well as the distance between the sensor and the fall. The distance problem can be solved by installing two or more sensors, but this increases the cost. To cover all possibilities, extensive studies have to be implemented. In addition, the overall multisensor system described in [62] turns out to be a little bit too costly for a typical house and the network infrastructure. We hope that the Internet of Things (IoT) will be widespread in the near future, which will make the entire system feasible.

Wearable accelerometer sensor signal processing

Even though several user-activated commercial devices are available for fall detection, they have limited benefits, especially



(a) (b) (c) (d)

FIGURE 6. Example frames captured during a fall from a standing position.

in situations where the user loses consciousness. As previously mentioned, all commercially available autonomous fall detection systems are based on wearable accelerometers. Such systems can also provide information about an individual's functional ability and lifestyle. Wearable devices also use tilt sensors to automatically detect a fall event. One drawback is that the individual has to wear the device continuously day and night. On the other hand, monitoring is not limited to confined areas, where the static sensors are installed, and can be extended wherever the subject may travel.

Dai et al. [47] developed a fall detection system using the accelerometers of a mobile phone. The app is capable of detecting falls when the phone is placed in a shirt pocket, on a belt, or in a pants pocket. When the average magnitude of the 3-D acceleration vector and the average value of the vertical acceleration in a short-time window exceed predefined thresholds a fall is reported. In [48] and [49], adaptive thresholds are developed. In [48], the threshold is determined using the body mass index of the user. Currently, mobile phone apps are not widely used by elderly people. In addition, methods based on using thresholds cannot be as reliable as systems that use machine-learning techniques, since threshold-based methods are more prone to producing frequent false alarms.

In [50], artificial neural networks (ANNs) are used for human-activity recognition. A single triaxial accelerometer is attached to the subject's chest. Acceleration signals are modeled using autoregressive (AR) modeling. AR model coefficients along with the signal-magnitude area and the tilt angle form an augmented feature vector. The resulting feature vector is further processed by the linear-discriminant analysis and ANNs to recognize various human activities.

Camera sensor-based methods

In recent years, one of the key aspects of elderly care has been intensive activity monitoring, and it is very important that any such activity monitoring be also autonomous. An ideal autonomous activity monitoring system should be able to classify activities into critical events, such as falling, and noncritical events, such as sitting and lying down. While fast and precise detection of falls is critical in providing immediate medical attention, other noncritical activities like walking, sitting, and lying down can provide valuable information in the study of chronic diseases and functional ability monitoring [51], [52] and for early diagnosis of potential health problems. Furthermore, the system should be able to smartly expend its resources for providing quick and accurate real-time response to critical events versus performing computationally intensive operations for noncritical events.

There has been a lot of work on activity monitoring by vision-based sensors [28], [53]–[61]. However, in all of these methods, cameras are static at fixed locations watching the subjects, thus introducing the issue of confining the monitoring environment to the region where the cameras are installed. The images acquired from the cameras are usually offloaded to a dedicated central processor. Also, 3-D model-based techniques require initializations and are not always robust. Another major practical issue is that the subjects who are being monitored often raise privacy concerns [54], as they feel they are being watched all the time.

In contrast to static camera-based methods, Ozcan et al. [5] take a different approach, introducing an autonomous fall detection and activity classification system by using wearable embedded smart cameras. Since the camera is worn by the subject, the monitoring is not limited to confined areas and extends to wherever the subject may travel, as opposed to static sensors installed in certain rooms. In addition, since the images captured will not be of the subject, as opposed to static cameras watching the subject, privacy issues for the subjects is alleviated. Moreover, captured images are processed locally on the device, and they are not saved or transmitted anywhere. Only when a fall occurs can an appropriate message be wirelessly sent to emergency response personnel, optionally including an image from the subject's camera. This image of the surroundings can be helpful in locating the subject. Also, the captured images carry an abundance of information about the surroundings that other types of sensors cannot provide. A recent study about privacy behaviors of lifeloggers using wearable cameras discusses privacy of bystanders and ways to mitigate concerns [62]. It is also expected that wearable cameras will be employed more to understand lifestyle behaviors for health purposes [63].

The proposed approach [5] is based on the oriented image gradients. Different from the original histograms of oriented gradients (HOG), separate histograms for gradient strength and gradient orientations are constructed, and the correlation between them is found. The gradient orientation range is between 0–180°, and it is equally divided into nine bins. The

FIGURE 7. An Android smartphone attached to the waist.

gradient strength histogram contains 18 bins. Moreover, instead of using a constant number of cells in a block, the cells that do not contain significant edge information are adaptively and autonomously determined and excluded from the descriptor in this proposed modified HOG algorithm. In [5], it is shown that the proposed method is more robust compared to using fixed number of cells in detecting falls. In addition to detecting falls, the proposed algorithm provides the ability to classify events of sitting and lying down using optical flow. The method is composed of two stages. The first stage involves detection of an event. An event can be one of the following: falling, sitting, or lying down. Once an event is detected, the next stage is the classification of this event. An example set of captured frames for falling from standing up position is presented in Figure 6.

Vibration sensors can be categorized into two groups based on the number of their axes: one-axis and three-axes sensor types.

As reported in [5], the fall detection part of the algorithm was implemented on the CITRIC embedded camera platform [64], which is a small, stand-alone, battery-operated unit. It features a 624-MHz fixed-point microprocessor, 64 MB synchronous dynamic random access memory, and 16 MB NOR FLASH memory. The wireless transmission of data is performed by a Crossbow TelosB mote. The images are processed locally onboard, and then dropped, thus, they are not transferred anywhere. For the falls starting from a standing position, an average detection rate of 87.84% has been achieved with prerecorded videos. With the embedded camera implementation, the fall detection rate is 86.66%. Moreover, the correct classification rates for the events of sitting and lying down are 86.8% and 82.7%, respectively.

More recently, we have implemented the fall detection part of this algorithm on a Samsung Galaxy S4 phone with Android OS and performed experiments with ten subjects carrying this phone. The experimental setup can be seen in Figure 7. We have also implemented a method to fuse two sensor modalities: the accelerometer and camera data. The average sensitivity rates for fall detection are 65.66%, 74.33%, and 91%, when we use only accelerometer data, only camera data, and camera data together with accelerometer data, respectively.

Zhan et al. [65] propose an activity recognition method that uses a front-facing camera embedded in a user's eyeglasses. Optical flow is used as the feature extraction method. Three classification approaches—k-nearest neighbor, logitBoost, and SVM—are employed. Further smoothing with hidden MMs provide an accuracy of 68.5–82.1% for a four-class classification problem, including drinking, walking, going upstairs, and going downstairs, on recorded videos.

Moghimi et al. [66] use an RGB-D camera mounted on a helmet to detect the users' activities. They use compact and global image descriptors, including GIST, and a skin segmentation-based histogram descriptor. For activity classification, learning-based methods such as bag of scale invariant feature transform words, convolutional neural networks, and SVMs were explored.

Ishimaru et al. [67] propose an activity recognition method using eye blink frequency and head motion patterns acquired from Google glass. An infrared proximity sensor is used for blink detection. The average variance of a 3-D-accelerometer is calculated to construct the head motion model. In the classification framework, four features (variance value of accelerometer, mean value of blink frequency, and the x-center and y-center of mass value of the blink frequency histogram) have been used to classify five different activities (watching, reading, solving, sawing, and talking) on eight participants with overall accuracy of 82%.

Conclusions

AL systems may provide safety and autonomy for elderly people while allowing them to live independently as well as relieve the workload of caregivers and health providers. However, to find widespread use, these systems should be robust and reliable. Current commercially available autonomous systems, which are not user activated, employ simple threshold-based algorithms for sensor data processing. As a result, they are prone to producing too many false alarms. Advanced signal processing techniques have to be developed to take full advantage of the recent developments in sensor technologies and provide robustness against variations in real-life conditions and the environment. Moreover, fusing multiple sensor modalities provides promising results with higher accuracy. Computational problems can be solved with the help of the IoT, which refers to wireless systems connecting industrial, medical, automotive, and consumer devices to the Internet. The IoT will allow objects and people to be sensed over existing Internet infrastructure. Vibration and PIR sensors, acoustic sensors and microphones, and cameras can be connected to form a network for an intelligent home designed for elderly people. The data and decision results that the sensors produce can be processed and fused over a cloud or a fog. We expect that the IoT will lead to remote health monitoring and emergency notification AL systems that will operate autonomously, without requiring user intervention.

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