Wearable Assistive System Design for Fall Prevention

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Abstract:

Fall is the prevalent issue among the elderly, and fall risk assessment and prevention are very important. Recent research discovers that bio-signal can be used to forecast falls via the pre-warning information. However, assistive devices for fall prevention are fully customized and difficult to implement in terms of wearability. In the paper, we will introduce the framework to design and implement wearable systems. Also we will present three case studies: smart insole, smart cane and smart headset to verify the feasibility of our proposed method. To the best of our knowledge, it is the first comprehensive literature for the discussion about fall prevention technology.

1. Introduction

Many elder people over 65 are at a high risk of falling because of their general frailty and multiple pathologies. Specifically, falls are reported by one-third of all people 65 and older, and have become a leading cause of deaths due to injury among elderly people. And the number of elderly people with fall-induced injury is increasing at a greater rate. Correspondingly, related health costs for fall-related medical treatments, such as fractures, open wounds and head traumas, which totaled $20 billion in 2006, has risen to $23 billion in 2010. As such, injuries due to falls also account for large healthcare costs and need to be cut off with low-cost solution based on novel biomedical technology. Therefore, falls among the elderly have become a growing concern, and preventative measures that cut fall hazards or reduce the probability of a fall are being urgently sought.

The most promising approach for fall prevention is the wearable assistive system which could detect and forecast the falling risk, since over 4 million individuals in the United States own the heath-care support with the wearable assistive system in their daily lives. However, the use of these assistive systems also introduces negative influence, such as additional cognitive burden to people who suffer from cognitive disability due to age or other causes. Fortunately, the limitations can be overcome with the advance of sensing technology, especially the emerging “wearable” sensors. The novel sensing technology can dramatically reduce the footprint of traditional sensors, and thereby integrate them into plastic, paper or even fabric materials. As such, when coupled with wireless communication and computing technology, these wearable assistive systems are possible to be used by individuals comfortably and invasively.

In this paper, we describe the development of several new wearable assistive systems that addresses the risks associated with falling. Specifically, the Smart-Headset system can detect the fall risk by monitoring the EEG signals of users, and release the warning before the real falling happens. In addition, fall risk is highly associated with physical gait parameters such as underfoot pressure distribution, cadence, and stride length. As such, the Smart-Insole system is capable of monitoring the underfoot pressure continuously and providing the fall risk assessment. Moreover, the Smart-Cane system can forecast the potential falling by investigating the improper usage of the canes by the elderly and disabled.
The remaining of the paper is as follows. Section 2 will introduce the general system design framework and design criteria. Section 3 will present a compressed sensing based bio-signal processing. After that, three case studies, including smart headset, smart insole and smart cane, will be introduced in details in Section 4 to valid the method we proposed. The conclusion is included in Section 5.

2. System Framework

In this section, we will state the system design framework of wearable system for fall prevention. In general, the system could include two parts, client end and server end. The client end will be taken with the user for bio-signal sensing, computing and transmitting. The server end is to mine the receiving data. Fig. 1 shows the stacked-layer architecture of client and server, where Fig. 1 (a) is the structure of the client, and Fig.1 (b) is the structure of the server.

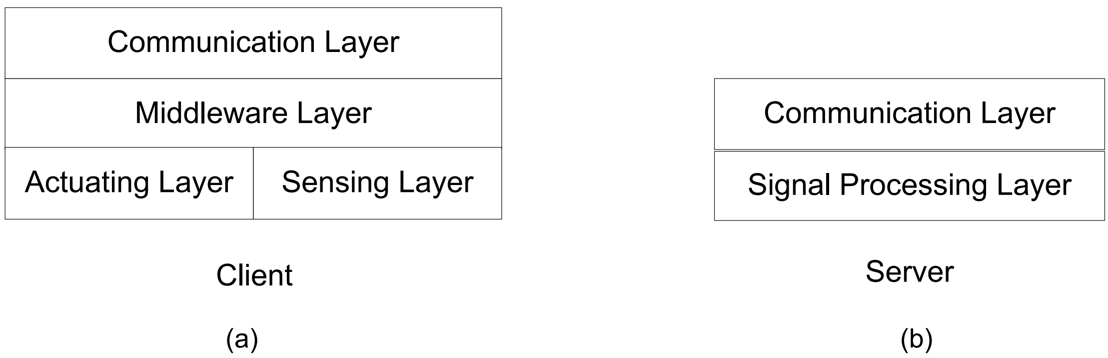

Figure 1: (a) Client Structure (b) Server Structure

2.1 Client End

The client part consists of four layers: sensing layer, actuating layer, middleware layer and communication layer. Sensing and Actuating layers are at the bottom to interact with users directly. Some sensors are included in sensing layer to acquire miscellaneous of bio-signals from users. With the sensed data, middleware implemented on microcontroller will perform preliminary processing such as signal filtering, sorting, compression and lightweight data analysis for feature extraction. Some of the expected results are urgent to report, and they will be sent to actuating layer to notice users, such as fall risk. Otherwise, the data will be sent through communication layer to server end for further data mining. The most common solution for communication layer is Zigbee, Bluetooth or WiFi, which highly depends on the specific applications.

2.2 Server End

For the server part, there are two layers. The first layer is the communication layer for receiving the data from client, and the secondary layer is signal processing layer. Data mining algorithm will be implemented in signal processing layer to analyze the fall risk of the user. After the calculation, the server end will send the feedback to client side for actuating.

2.3 Problem Analysis

In the whole structure, there are two time-consuming procedures. One is the wireless data transmission between client and server; the other is the data mining on the server side. It is known that the time response time is critical for fall prevention. To alleviate this problem, in this paper, we will present an innovative method for high-efficiency data processing. Furthermore, we developed several wearable fall prevention systems for elderly people, which is affordable, lightweight and long life. Our solution is to leverage the recently established theory of Compressed Sensing (CS) [5].

3. CS Based Bio-Signal Processing

Before discussing our proposed method in detail, we would like to revisit the classical signal processing paradigm. The traditional signal processing sequence includes data acquisition, data compression, data mining and information retrieval. Most scenarios are as follows: Firstly we get an over-completion signal through an ADC under the intuition 'the more data we collect, the more information we have'. The temporal sampling rate is determined by the Shannon/Nyquist theorem. However, most computer processors are not sufficient to process the large volume of information. The most straightforward way to reduce the data volume is to compress the data by removing redundancies. For example, the energy located in image data in the high frequency regions is usually small and can be neglected, without lowering the quality of the image too much. Well-known encoding methods, such as MPEG, JPEG and MP3, are based on this fact. Afterwards, algorithms are executed on the trimmed dataset to retrieve the information we originally wanted. In short, we collect a large amount of information, abandon a large part of it, and then examine whether the rest is useful. It is not intelligent in the sense that we have done a lot of unnecessary work in this procedure. Is it possible to collect only the necessary information we need? The answer is that it is not trivial, but possible.

3.1 Bio-Signal Projections

It has been proven that structured signal characteristics reside in a much lower-dimensional space compared to the original dimension N and thus such signals are compressible. This motivates us to use recently developed compressive sensing principles by Candes and Donoho [4], [5] which allow us to make K << N measurements (i.e., heavily under-sample the true data) and still be able to estimate x with high fidelity. For illustrative purposes, we consider a real-value, fine-length and discrete-time bio-signal x, which can be represented as an N×1 column vector with elements x[n]. Also, it can be projected into another orthogonal space spanned with a set of orthogonal basis vectors. In other words, the BIO-SIGNAL signal can be represented in terms of a basis of N×1 vectors $\{\psi_i\}$ (i =1…N). Thereby, using the N×N basis matrix $\psi = [\psi_1, \psi_2, \ldots, \psi_N]$ with the basis vectors $\{\psi_i\}$ as columns, the BIO-SIGNAL signal x can be expressed as linear combination of basis vectors with coefficients $\{ \alpha_i \}$

$$x = \sum_{i=1}^{N} \alpha_i \cdot \psi_i \quad \text{or} \quad x = \psi \cdot \alpha \quad \text{where} \quad \alpha_i = < x, \psi_i > = \psi_i^T \cdot x \tag{1}$$

Where α_i the vector of weighting coefficients and is equivalent to x as the representation of the bio-signal. Clearly, x is in the time or space domain while α_i is in the orthogonal space or ψ domain. Usually, the representation of bio-signal in ψ domain is K-sparse ($K \ll N$), which implies that α_i vector has only K large coefficients and thus signal x is compressible.

3.2 Bio Signal Representations

As we mentioned above, compressive sensing can directly acquire a compressed signal representation (useful information) without having to acquire all N samples. In this section, we briefly explain the measurement operations that acquire the compressed representation while keeping the salient information.

Consider a general linear measurement process that computes $M<N$ inner product between x and measurement vector as:

$$y_j = \langle x, \phi_j \rangle \quad \text{or} \quad y = \Phi \cdot x = \Phi \cdot \psi \cdot \alpha = \Theta \cdot \alpha \quad (\Phi \in R^{M \times N},\ y \in R^M) \tag{2}$$

As such, the original bio-signal x can be represented by a set of compressed measurements $\{y_j\}$, and there exists a one-to-one relationship between them, which means the original signal x can be uniquely reconstructed by measurements $\{y_j\}$. This also provides the foundation for fall prevention analysis, and makes it possible to detect fall risk by investigating only the small-scale measurements $\{y_j\}$ rather than the large amount of original signal information.

3.3 CS Based System Design

Based on the foregoing analysis of the above, we can propose a bio signal processing system based on compressive sensing, and the system overview can be plotted as shown in Fig. 2.

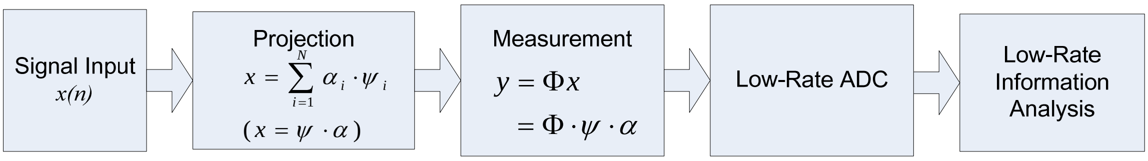

Figure 2: Overview of bio- signal acquisition system based on compressive sensing

It can be observed that the original bio signals from the input need to go through projection and measurement stages, where the original signal will be transformed into the ψ domain and further measured with matrix Φ. As such, the data y is a small-scale yet equivalent representation of the raw bio-signal x. Therefore, signal y is sparse. [6] theoretically proved that if y is explicitly-sparse with only M non-zero elements in the transform space, selecting $K \geq M \log N/M$ samples at random from y provides sufficient information. It is with high probability that we can then enable signal reconstruction with the minimal error [6].

Therefore, the ADC in this application can use low sampling rates and generate small-volume yet complete data for the information analysis. The most challenging steps in the acquisition system are the designs of projection matrix ψ and measurement matrix Φ. First, the projection matrix ψ should make the signal x become much sparser in the constructed orthogonal space, which depends on the specific signal structure under study. Second, the measurement matrix Φ should be stable, incoherent and satisfy the restricted isometry property (RIP) [6] to guarantee the one-to-one mapping between the original bio signal and corresponding measurement **y**.

Therefore, valid pattern recognition can be conducted on the low-rate measurements, rather than on the original rapidly sampled signal, to detect the signature of an impending fall from bio-signal data. Then, a forecast of the potential fall risk can be provided based on results from pattern recognition, and corresponding preventive measures can be taken to help the elderly individual to regain the physical balance.

4. Prototype

To empirically prove the feasibility of the design framework we proposed the above, we will introduce three implementations for fall prevention technology. The pilot experiments show that CS-based signal processing strategy could reserve the fidelity of the data but dramatically reduce the size of the raw data. For the sake of the page limit, more detailed experimental results can be found in the supplemental materials.

4.1 Smart Insole System

Considering that gait signal is the bio-parameter most related to fall, we prototyped a Smart Insole system to analyze the gait of the users. [9] lists the most ten gait parameters needed for fall risk assessment from our medical professionals.

To address these ten criteria, it is necessary to analyze the underfoot pressure distribution and fully motion tracking during walking. In the implementation, we put 40 pressure sensors, 3D accelerometer, 3D gyroscope and 3D magnetometer in the insole. Fig. 3(a) shows the circuit prototype of the insole. We use TI MSP430 as the central controller to sample and transmit the sensing data. In order to achieve the fully motion tracking for gait parameter calculation, the sampling rate should be 100Hz. The sampling is 12 bit, and the data transmitting rate is 58800 bps. Note that 40 pressure sensors is the minimal requirement to analyze the comprehensive weight distribution. The data rate should be much higher if the more accuracy is required.

Considering the real-time response requirement, we implemented the above proposed strategy in the system. In the insole (client) part, the microcontroller will sample and compress the sensor data via compressed sensing. After that, the cooked data will be transferred through Zigbee network. Therefore, the data for transmitting is much less than raw data. In the server part, the receiver will get the data for decoding.

Fig. 2(b) is the smart insole with good packaging. The total thickness of the system is with 1cm, which is comfortable to wear for the human being. Fig. 2(c) shows the smart insole in demo. The server part is implemented in the laptop. As shown in the scan, the 3D fully motion and pressure distribution can be calculated and illustrated on the screen.

Figure 3: (a) Insole Circuit Structure (b) Smart Insole in Packaging (c) Smart Insole in Demo

4.2 Smart Cane System

In this section, we present the Smart-Cane system [8] that utilizes commercially available micro sensor, computing, and wireless technologies to address the falling risks for elderly people. Specifically, the Smart-Cane system is designed to detect and classify cane usage patterns, such as orientation, motion and rotational forces. As such, it can predict possible outcomes such as high risk of falling so that to alert the patient, caregiver, and clinician about the potential falling of the patient. We will discuss the hardware and software designs of the Smart-Cane as follows:

4.2.1 Hardware Architecture

In order to enable daily usage for common people, the Smart-Cane system is developed with low cost, long operating lifetime embedded computing systems, such as six motion sensors including a 3-axis accelerometer, three single-axis gyroscopes, and two pressure sensors. These sensors can acquire motion, rotation, force, strain, and impact signals, and further calculate the orientation with respect to the gravity and swing characteristic of the cane.

The 16-bit, 0-5 volt data from the sensors can be acquired up to 300 samples per second (Hz) and streamed in real-time to a personal devices (e.g. cell phones and PDA) or severs (e.g. laptop/desktop computers) by Bluetooth data acquisition modules continuously for over 20 hours. In our experiment, we interfaced the Smart-Cane system with a standard PDA.

The entire system is shown in Fig. 4 (a) where six sensors are marked in the figure. Also, the interfaced PDA device showing the acquired signals is shown in Fig. 4 (b).

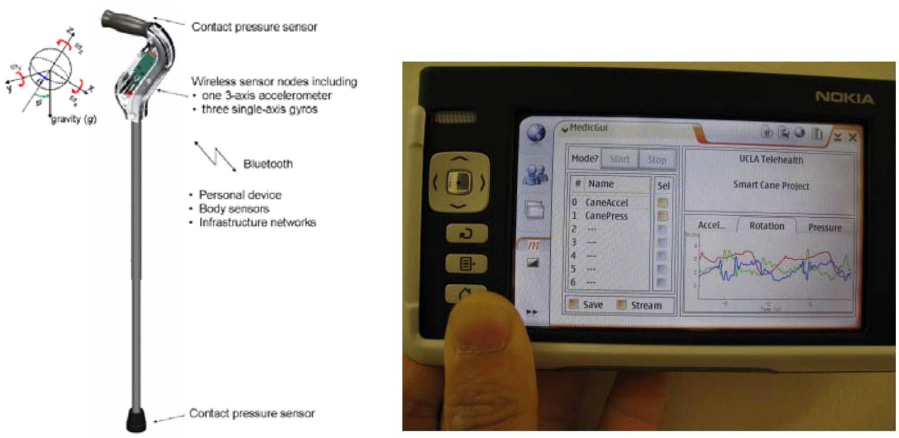

Fig 4: (a) The Smart-Cane system; (b) Acquired data analysis in PDA device.

4.2.2 Software Design

With the acquired sensor signals received from Bluetooth Serial Port, the computing server can generate the low-pass filtered raw sensor signals so that to track the cane's orientation, motion and rotational forces. First, the Smart-Cane system can formulate the cane usage patterns across a large group of patients and develop statistical models that can identify and detect the improper usage behavior leading to instability and falls in the elderly. Then, when the Smart-Cane system is engaged, it can recognize the improper usage patterns accurately and alert the falling risk in the real-time to avoid the potential injuries.

4.3 Smart Headset System

As stated in the above, from an ergonomic point of view, fall risk is highly associated with physical gait parameters such as underfoot pressure distribution, cadence, and stride length. A number of remarkable discoveries have been made by investigating these physical gait parameters for fall risk assessment in recent years [1, 2]. More importantly, the research reveals that physical gait parameters can forecast fall risk up to 0.3 seconds before the fall really happens. However, 0.3 second is insufficient to take any action to prevent the fall.

Recent studies empirically prove that many mental and physiological signals, such as Electro-encephalogram (EEG), Electro-cardiogram (EKG) and Electro- myography (EMG), are also related to falls and surprisingly discover that EEG signals can offer much earlier forecast of a potential fall risk compared to physical gait parameters [3]. As shown in Fig. 5, there is a significant anomaly in EEG signals about 3 seconds prior to the fall. Therefore, it is possible to assess fall risk and activate fall prevention measures through warning patterns from EEG signal.

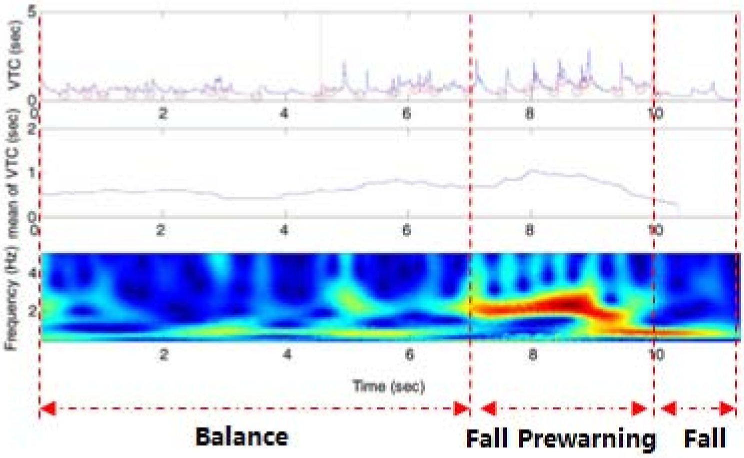

Figure 5: EEG signal including: (1) original time series in falling trial; (2) evolution of mean values of EEG signal; (3) time-frequency plot of EEG shows the power changes during transition-to-falling stage.

Fig. 6 (a) illustrates the EEG acquisition system, called Smart Headset. There are two main parts: ADC module and data processing module. ADC used in our system is a kind of adaptive sampling module from Neurosky Inc [7]. This ADC has a low-sampling noise, high accuracy and configurable data rate. The other part is the data processing module. The key chip on the module is a ultra low power microcontroller, MSP430 from TI. The proposal CS based algorithm is hosted on this module for compressed data analysis. Additionally, Fig. 6 (b) shows that the whole system with good package is very tiny compared to the size of a quarter, in the mean while the signal accuracy is as accurate as those from the conventional scalp EEG device. Fig. 6(c) shows the smart headset in use.

(a) (b) (c)

Figure 6: (a) Circuit Structure (b) Smart Headset for Fall Prevention (c) Smart Headset in Use

5. Conclusion

In this paper, we introduced three innovative assistive systems for fall prevention via bio-signal analysis. We proposed the design framework for wearable system design. In proposed method, the physiological data can be reduced significantly within the minimal data loss, where the optimality of data reconstruction is theoretically guaranteed. Furthermore, we prototyped several CS-based bio-signal analysis system and empirically verified that bio-signal is structurally sparse. Our wearable systems for fall prevention could keep high accuracy in the pilot study.

6. Acknowledge

The authors would like to thank Dr. William Kaiser of UCLA Wireless Health Institute for his supportive suggestions.

7. Reference

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