

Automation for Monitoring Elderly Americans

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Abstract More elderly Americans are living alone than ever before. Since elderly Americans are exposed to more risks of falling as they get older, reliably detecting falls for elderly Americans has become an important field of research. Currently, there are some devices that can assist the elderly, but they are not real-time, accessible, or particularly effective. We designed a novel automatic system for monitoring healthy independent living. The system will contain the devices for fall detection, surrounding environment monitoring, as well as measuring a person's blood pressure, pulse, and oxygen saturation in real time. With this automatic monitoring system, a person's state is not only controlled by that individual; rather, everything is automated so that even if a person falls unconscious or becomes extremely injured, it will still take the necessary steps to call for assistance. The system we proposed is aimed towards both healthy individuals as well as those with disabilities and chronic conditions.

Keywords: automatic system, monitor, healthcare

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1. Introduction

The aging American population is already bringing pressure on healthcare and social services. As the number of elderly individuals continues to rise, the situation is likely to get worse. The elderly population (people 65 years or older) numbered 40.4 million in 2010, which was a 15.3% increase since 2000. The number of Americans aged 45-64 who will reach 65 over the next two decades increased by 31% during this decade. Over one in eight Americans is an elderly American. Persons reaching age 65 have an average life expectancy of an additional 18.8 years. The population 65 and over is projected to increase to 55 million in 2020 (a 36% increase for that decade). By 2030, there will be about 72.1 million older persons, over twice the number in 2000 [1].

Falls occur frequently in the elderly population and significantly impair their quality of life. It is estimated that more than one in three elderly individuals living at home fall at least once a year. About 10% of falls result in serious injury (e.g. fractures). Falls are a leading cause of injury-related hospital admissions and deaths for older people [2]. The risk of falling also rises with increasing age. Falls also lead to decreased mobility, fear of falling, and death [3,4,5].

Treatment of the injuries and complications associated with falls costs the U.S. over thirty billion dollars annually. Sixty percent of falls occur at home and the possibility of not having any assistance in case of unconsciousness or extreme injury are primary reasons why many otherwise healthy individuals are forced to leave the comfort and privacy of their own home to live in an assisted-care environment. Furthermore, a fall can have a psychological

impact even if the senior is not physically injured. After a fall, many seniors become so afraid of falling again that they limit their activities. This in turn decreases their fitness, mobility, and balance and leads to decreased social interactions, reduced satisfaction with life and higher likelihood of depression. This fear cycle then increases the risk of another fall [6].

2. Background

Accelerometers with low-cost and low-power features make a wearable and reliable fall detection system possible. Multiple sensors with accelerometers placed at various locations in the body are used for real-time human movement detection [7,8,9]. Many systems [3,10,11,12,13] employ triaxial accelerometers to detect fall according to the acceleration of body motion and posture angle. To achieve better accuracy, later systems [14,15,16] detect fall using accelerometers with barometric pressure sensors, image processors, and gyroscopes.

Information Technology for Assisted Living at Home (ITALH) is a project using new technology to help older citizens live more comfortably [17,18]. The ITALH includes two items: the IVY project concerns detecting falls at home or in office environments, and the SensorNet project concerns developing an integrated, safe, and wireless sensor to monitor the user. However, those previous systems have several restrictions [19]: the methods are device-centric, not user-centric; the devices are expensive and complicated; and the information received by the doctor is insufficient to make an accurate diagnosis in a timely fashion. In most of the systems, the final decisions are based on the data collected from the

sensors and the user cannot express his ideas on his own initiative. He can only passively accept the decision. In addition, some of the previous systems use acoustic or vibration sensors and image processing software. Most of them are very costly and not universally accessible. Ordinary users cannot control them at their own will. Few systems send an SMS message as a simple alarm. However, the text message is not enough to describe a patient's symptoms, so caregivers cannot have an accurate assessment of the situation.

Home healthcare sentinel system (HONEY) [19] is a home-based fall detection system. It uses a triaxial accelerometer to trigger the detection and deploy speech recognition systems and images to reduce the false positives. In that system, if the triaxial accelerometer does not detect the fall, the alert will not be sent out. If a person falls slowly, the fall will not be detected.

For real-time reconstruction of 3D scenes from video, Narayanan et al. [20] computed depth maps using multi-baseline stereo and merged them to produce viewpoint-based visible surface models. Holes due to occlusion are filled from nearby depth maps. Koch et al. [21] presented a volumetric approach for fusion as part of an uncalibrated 3D modeling system. Sato et al. [22] proposed a volumetric method based on voting. Each depth estimate votes not only for the most likely surface but also for the presence of free space between the camera and the surface. Werner and Zisserman [23] proposed an approach to reconstruct buildings. It uses sparse points and line correspondences to discover the ground and facade planes. Vaishet al. presents a method which adopts techniques from classical stereo reconstruction, matching corresponding pixels in all images of the light field using essentially robust patch-based block matching [24]. Cornelis et al. [25] presented a system for near real-time city modeling that employs a simple model for the geometry of the world.

3. Proposed Approach

Due to the limitations of the above technologies, we design a system that monitors the potential risks to healthy, elderly citizens and notifies us of emergency situations in real time. Figure 1 shows the framework of the system. By wearing Watching-Over-Me (WOM), a person will be monitored not only in his or her home but also in places where the person spends plenty of time.

The system will contain the devices for fall detection, environmental monitoring, as well as measuring a person's life characteristic markers.

3.1. Fall Detection

A triaxial accelerometer is integrated into the fall sensor, and the fall sensor sends early warning information if the trigger conditions are met with handling the three axes' sample values. Many smartphones have the triaxial accelerometer. We can use these smartphones, such as the HTC G3 Hero smartphone, as fall sensors. In addition, the Bluetooth module and a high performance processor on the G3 satisfy the fall sensor's requirements.

It is known and verified that a sensor based on a triaxial accelerometer can distinguish the body movements more precisely when it is fixed on the patient's waist [26]. The

triaxial accelerometer will put out three acceleration values on the x-, y- and z-axis at every sampling point. When the body is stationary, the total acceleration of the body is vertical down. When the body is moving, the acceleration changes along with the movement intensity. Fall sensors are based on the assumption that a fall is usually associated with a magnitude impact. An estimation of the degree of body movement intensity can be obtained from the signal vector magnitude (SVM). Define SVM by the relation:

$$SVM = \sqrt{x_i^2 + y_i^2 + z_i^2}$$

where x_i is the i -th sample value of the x-axis signal (similarly for y_i and z_i). Therefore, comparing the SVM to a preset SVM threshold allows detecting the associated fall. Similarly, when the body falls, the space relationship between body and ground also changes significantly. In order to determine the space posture of the body, Tilt Angle (TA) is defined as the angle between positive z-axis and SVM by the relation:

$$TA = \arccos(z/SVM)$$

where z is the sample value of the z-axis signal. TA refers to the relative tilt of the body in space.

We also need an angle distinction between the upright postures of sitting and standing, as well as lying in various conditions. Karantonis's works [9] provide the range of TA corresponding to the different body postures: if the patient's TA is from 0 to 20°, it is classified as standing, and values from 20 to 60° indicates a sitting posture; if TA is between 60 and 120°, it is regarded as a lying posture. In most cases, a fall starts from a standing posture, and directly ends with lying on the floor. However, no fall would be predicted if the user falls in such a way that he or she was not parallel with the ground. This is important in various cases during a fall. A user will try to grasp a wall, chair, or other objects and end up slumping next to the object, such as sitting on a chair, rather than lying on the floor. Therefore, a sitting posture following a magnitude SVM is regarded as a fall.

3.2. Surrounding Environment Monitoring

WOM (see Figure 1) can be attached to an elder person's side at all times. One set of sensors are image sensors – tiny cameras, which are mounted on the elder person's clothes or in a hat. With today's camera hardware it has become possible to capture real-time images of the surroundings. Our method is based on detecting surrounding environmental information. Our advanced algorithm will make the system learn from environmental data, and then construct the 3D scene.

There has also been a considerable amount of work involving 3D reconstruction from aerial images [27,28]. The system collects video streams and generates automatic, real-time 3D reconstruction from videos of scenes. The core algorithms operate on the frames of a single video-camera as it moves in space. The reconstructions are based on frames captured at different times by the same camera under the assumption that the scenes remain static [29]. Compared to laser scanning, an attractive property of passive, image-based stereo techniques is the ability to create a 3D representation

solely from photographs and to easily capture the scene from different viewpoints [30].

3.3. Health Data Monitoring

Another set of sensors monitors the individual's vitals, such as blood glucose, blood pressure, pulse, oxygen saturation and sweat pH.

Additionally, new glucose-monitoring devices [31] can measure blood glucose levels in a non-invasive fashion. The wearable glucose sensor, which measures glucose concentration and hydration levels, consists of a laser device that produces a wavefront of light to illuminate the skin and nearby arteries on the wrist, and a camera that monitors changes in the light as it scatters off the skin. The rehydration levels are measured because the strength of the signals produced are affected by muscle weakness, one of the major signs indicating mild to moderate dehydration. It uses the speckle effect to directly monitor the glucose concentration in the bloodstream, as well as the wearer's relative hydration level.

Pulse Tracker [32] could be used to monitor pulse non-invasively with a sensor that measures heart rate without being affected by movement. It uses the 'speckle effect', where interference patterns are produced on images when laser light reflects from an uneven surface or scatters from an opaque material. The scatter patterns of light change when the reflected material is moving (such as blood through blood vessels). Speckle effect could be used to measure flow pulsations even when the light source used to create the speckle pattern was moving.

Wrist blood pressure monitors produce the most accurate reading whether you are at home or outdoors [33]. Wrist blood pressure monitors are sensitive to wrist position with its motion-sensor technology, and automatically keeps a history of the individual's measurements. It also gives the wearer the option of sharing the data with his or her primary care provider. Measuring methods are oscillometric and automatic inflation [33]. There is also an automated blood pressure and pulse detector on the wrist [34].

Oxygen Saturation Monitoring [35] is based on a synergy of photoplethysmography (PPG) and blood flow sensors. It can be built into the bottom of a wristwatch to measure oxygen saturation and pulse at the wrist. This technology exploits the synergy of a set of noninvasive optical sensors. The PPG sensor is designed such that it collects the same amount of physiological information as conventional fingertip probes. Another side of the solution is using a complementary blood flow sensor. This sensor uses a coherent light scattering technique, the "dynamic speckle", that allows continuous measurements of blood rheological parameters.

The use of wearable sensors to monitor various health related biometric parameters during daily activities has attracted increasing interest recently. A number of methods currently exist for the measurement of sweat pH. The most popular of these is the pH-probe, which can be placed in contact with the skin in order to measure sweat pH [36].

Sweat pH monitoring device [37] is an ideal wearable sensor for measuring the pH of sweat since it does not contain any electronic part for fluidic handling or pH detection and because it can be directly incorporated into

wristbands, which are in continuous contact with the skin. In addition, due to the micro-fluidic structure, fresh sweat is continuously passing through the sensing area providing the capability to perform continuous real-time analysis. It is able to provide immediate feedback regarding sweat composition. Sweat analysis is attractive for monitoring purposes as it can provide physiological information directly relevant to the health and performance of the wearer without the need for an invasive sampling approach.

A wearable electronic-free micro-fluidic device for the continuous monitoring of pH in sweat during exercise is described by Curto et al. [38]. The sensing capability is based on ionic liquid hydrogels, containing pH sensitive dyes capable of reporting pH activity in the range of 3 to 10.

Salvo et al. [39] developed a prototype for wearable sweat rate sensors integrated onto a textile. It can be worn directly on the body and continuously monitors sweat rate. They rely on the measurement of the water-vapor pressure gradient near the skin in unventilated chambers: the steeper the gradient, the higher the water evaporation rate from the skin. To assemble the sweat-rate sensor, a pocket was created on two fabric nets. The first humidity sensor was at a distance of 0.2 cm from the skin, while the second was 1 cm from the skin. Since sensitivity is inversely proportional to the distance between sensors, a compromise was made in order to have good sensitivity and a difference in the humidity values greater than inaccuracy in the single humidity measurements. The mesh of the net was large enough to offer negligible resistance to the diffusion of the water-vapor flow.

3.4. The Processing

Our system first acquires real-time data from the surrounding environment and the health information from the person wearing WOM. The devices periodically compare the real-time data to the acquired data. When an abnormal event occurs, it will make a decision and alert the pre-determined parties (ambulance, caregiver, family members, etc.).

The system will base its ability to detect progressive declines in physical and cognitive abilities by determining the abnormal scene. To achieve this, the system compares recent input data of the scene with the data of the routine scene. For example, suppose a person falls down or is staggering. The system integrates the environmental input with the health data to make the decision if the person is in critical condition. If the system detects this kind of situation it automatically calls 911. It also triggers an alert system in the WOM. If there are people around, they will also be alerted.

The monitoring unit transforms the data into a real-time 3D scene and 3D character. The data is continuously fed and the character and surrounding environment are updated all the time. The person's activities can be viewed on mobile devices. The person wearing the WOM can control who can see his or her activities.

4. Conclusion

We have presented a novel design for healthy independent living. It is reliable, safe, and simple. It is

easy to use and has intuitive user interfaces with consideration for a user's disability or impairment. The design provides feedback in meaningful forms, whether auditory, visual, or tactile. Most importantly, our system for healthy independent living engages, empowers, and motivates the individuals with respect to his or her abilities.

The advantage of our system is that we are able to detect the person's dynamic state. Our method is based on

surrounding environmental input, fall detection, and health data as auxiliary information. As long as the person is wearing WOM, the entire system is automated. Even if the person suddenly falls unconscious, the device will still take the appropriate actions. Thus, this technology has multiple benefits and can be targeted for both disabled and healthy individuals alike.

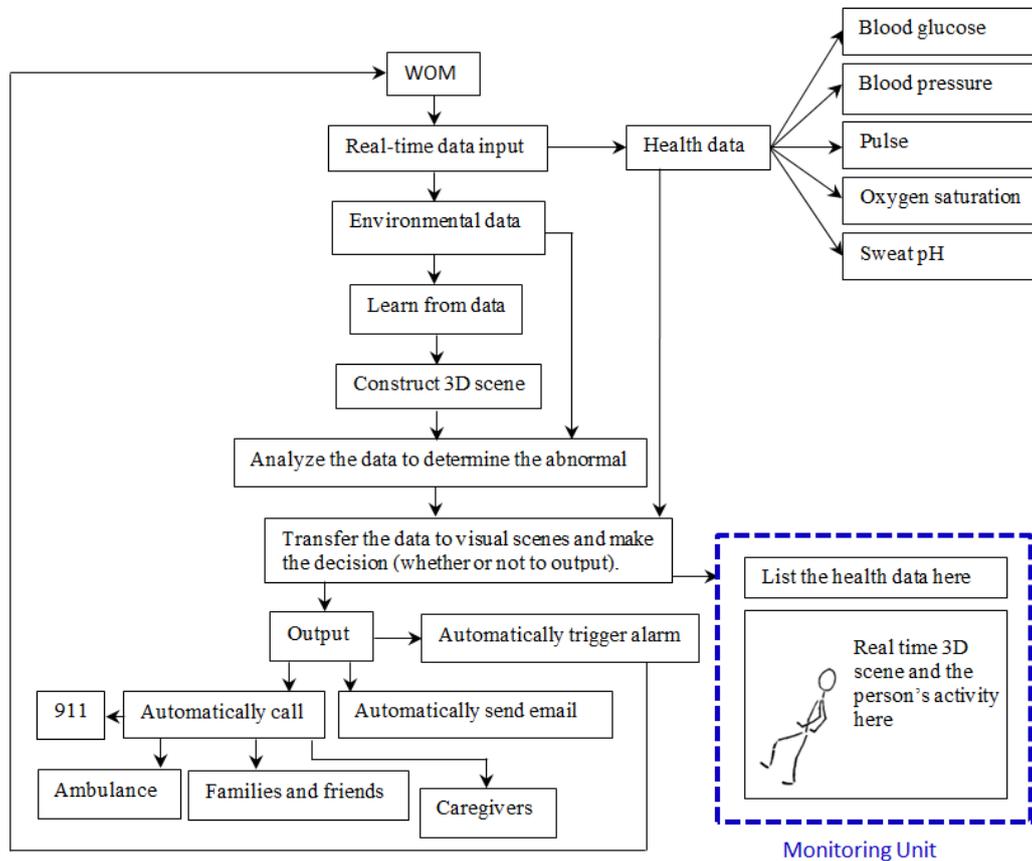


Figure 1. The framework of the system

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