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Monitoring System for a Latent Risk Population

Alice J. Lin[1], Charles B. Chen[2] and Fuhua (Frank) Cheng[3,4]

[1]Marshall University, lina@marshall.edu
[2]West Virginia University, cchen6@mix.wvu.edu
[3]University of Kentucky, cheng@cs.uky.edu
[4]National Tsing Hua University, cheng@cs.nthu.edu.tw

ABSTRACT

There are more than 11 million elderly Americans living alone. They belong to a latent risk population that will encounter emergency situations on a frequent basis. Thus, latent risk populations require constant monitoring. Currently, there are many devices that can assist the elderly, but they are not real-time, easily accessible, or particularly effective. Here, we present a novel design for healthy independent living. The system will contain 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 technology, a person's state is not only controlled by that individual; rather, everything is automated so that even if a person falls unconscious, the system will still take the necessary steps to call for assistance. The technology we propose is aimed towards both healthy individuals as well as those with disabilities and chronic conditions.

Keywords: monitoring system, 3D reconstruction, 3D scenes.

1. INTRODUCTION

The elderly population (people 65 years or older) numbered 40.4 million in 2010, an increase of 5.4 million or 15.3% 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 person. Persons reaching age 65 have an average life expectancy of an additional 18.8 years. The population of 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 elderly people, over twice the number in 2000 [30].

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 with the risk of falling increasing with age. Falls also lead to decreased mobility, fear of falling again, and death [7],[20],[29]. Treatment of the injuries and complications associated with falls costs the U.S. over thirty billion dollars annually. The danger and severity of falling 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 which in turn decreases their fitness, mobility and balance. This leads to decreased social interactions, reduced satisfaction with life, and a higher likelihood of depression. This fear then increases the risk of another fall [23].

Health care and medicine rely on effective detection and characterization of a person's physical and mental states and significant changes to those states. Current methods to assess these indicators of well-being are performed at the convenience of the health-care provider who often assumes that observations during an office visit represent typical function. Furthermore, these methods may involve contrived or burdensome tests or depend heavily on recall. Thus, current methods may miss significant acute events or important signals of declining function or may poorly characterize detected events.

Due to 3D capabilities becoming ubiquitous and computers with basic graphics hardware running 3D

Computer-Aided Design & Applications, 12(6), 2015, 693–699, http://dx.doi.org/10.1080/16864360.2015.1033332

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applications, we designed a computer-aided real-time automated monitoring system. Our monitoring system is intended to overcome these limitations. It has the potential to capture rare, irregular, or transient events; symptoms that are difficult for a patient to report; and changes in condition that evolve slowly over time. These improvements, in turn, could yield more accurate and earlier detection of changes that may interfere with healthy and independent living. The development of our technologies will significantly enable functional independence and improve the quality of life for people with disabilities, people aging with mild impairments, as well as individuals with chronic conditions.

The technology enables monitoring of personal motion, vital signs, and physiological measures in a manner that minimizes disruption to an individual's daily routine and at all times protects their privacy and comfort. The system is expected to integrate, process, analyze, communicate, and present data so that the individuals are engaged and empowered in their own healthcare with reduced burden to healthcare providers.

2. RELATED WORK

Accelerometers with low-cost and low-power consumption features can make a wearable and reliable fall detection system. Multiple sensors with accelerometers placed at various locations in the body are used for real-time human movement detection [11],[13],[14]. Many systems [4],[7],[18],[27],[34] employ tri-axial accelerometers to detect falls according to the acceleration of body motion and posture angle. To achieve better accuracy, later systems [1],[17],[33] detect falls 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 [9],[10]. 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, these systems have several restrictions[36]: The methods are device-centric, not user-centric. The devices are expensive and complicated. 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 their ideas on their own initiative and must passively accept the decision. In addition, some of the previous systems use acoustic or vibration sensors and image processing software which are high cost and not universally accessible. Thus, ordinary users cannot control them on their own. Also, a few systems send a text message as a simple alarm; however, the text message is not enough to describe a patient's symptoms, so caregivers cannot get an accurate assessment of the situation.

Home Healthcare Sentinel System (HONEY) [36] is a home-based fall detection system. It uses a tri-axial accelerometer to trigger the detection and deploy a speech recognition system and images to reduce the false positives. The trigger depends on the signal vector magnitude (SVM). In this system, if the tri-axial accelerometer doesn't detect the fall, the alert will not be sent out. An example would be a person falling slowly which the system would not detect.

For the real-time reconstruction of 3D scenes from videos, Narayanan et al. [19] computed depth maps using multi-baseline stereo images and merged them to produce viewpoint-based visible surface models. Holes due to occlusion are filled in from nearby depth maps. Koch et al. [16] presented a volumetric approach for fusion as part of an uncalibrated 3D modeling system. Sato et al. [28] 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 [32] proposed an approach to reconstruct buildings. It uses sparse points and line correspondences to discover the ground and facade planes. Vaish et al. presented 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 [31]. Cornelis et al. [6] presented a system for near real-time city modeling that employs a simple model for the geometry of the world.

3. OUR APPROACHES

Due to the limitations of the above approaches, we designed a system that monitors the potential risks to healthy elderly citizens and notifies emergency crews in real-time. 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 (such as stores, parks, etc.). The system will contain the devices for fall detection, surrounding environmental monitoring, as well as measuring a person's blood pressure, pulse, and oxygen saturation in real-time. Furthermore, the systems will integrate information from multiple sensors, appropriate clinical information, and ambient data such as temperature and/or global position. Fig. 1 is the framework of the processing system. First, the system acquires real-time data from the surrounding environment and the health data from the person wearing WOM. This information is stored as standard scenes and each time the person appears in the same scene the system compares the surrounding environmental information with the information in stored standard scenes. The system continually learns from environmental

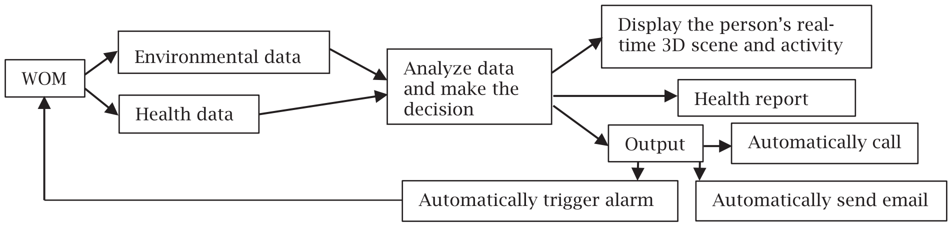

Fig. 1: The framework of the system.

data and then constructs the 3D scene. The 3D scene is accumulated as the person passes through more and more places.

The devices periodically compare the real time data with the learned data. When an abnormal event occurs, it will make a decision and inform the pre-determined parties (ambulance, caregiver, family members, etc.). The system will base determining abnormal scenes on its experience to detect progressive declines in physical and cognitive abilities. 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 data with 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 or families and friends and also triggers an alert system in the WOM. If there are people around, they will also be alerted. If the situation is considered "normal", the system reports the person as healthy. The person's activities, surrounding environment, and a list of health data can be viewed on the internet with office computers or mobile devices. The person wearing the WOM can control who can see his or her activities.

3.1. Fall Detection

A tri-axial 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 a tri-axial accelerometer. We can use these smartphones, such as the HTC G3 Hero smartphone, which has a tri-axial accelerometer, as fall sensors. In addition, the Bluetooth module and a high performance processor on the G3 satisfy a fall sensor's requirements very well.

It is known and verified that a sensor based on a tri-axial accelerometer can distinguish body movements more precisely when it is fixed on a patient's waist [5]. The tri-axial accelerometer will output three acceleration values of x-, y- and z-axis at every sampling point. When the body is stationary, the total acceleration of the body is the gravity of Earth, vertical down. When the body is moving, the acceleration changes along with the movement intensity[36]. 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 equation:

$$SVM = \sqrt{{x_i}^2 + {y_i}^2 + {z_i}^2} \tag{3.1}$$

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 detection of 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 equation:

$$\mathrm{TA} = \arccos(z/\mathrm{SVM}) \tag{3.2}$$

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

Karantonis [14] provides the range of TA corresponding to the different body postures: if the patient's TA is from 0 to 20°, the patient is classified as standing, values from 20 to 60° indicate a sitting posture, and if TA is between 60 and 120°, the patient is regarded to be in 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 might try to grasp a wall, chair, or other objects and end up slumping next to the object, rather than lying on the floor. Therefore, a sitting posture following a magnitude SVM is regarded as a fall.

3.2. 3D Scene Reconstruction

WOM (Fig. 1) portable signaling devices with two sets of complementary sensors are on the elder person's side at all times. One set of biochemical sensors detect biochemical markers in the elder person, such as blood glucose, blood pressure, pulse, oxygen saturation, sweat pH and salt balance. Biochemical abnormalities occur when the individual's biochemical and physiological parameters exceed the threshold and reach a dangerous level. Another set of sensors are image sensors – tiny cameras that are becoming increasingly smaller. Due to modern day standards, they can be mounted on the person's clothes or in a hat and capture real-time images of the surroundings.

There has been a considerable amount of work involving 3D reconstruction from aerial images [12],[37]. The system collects video streams and 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 time instances by the same camera under the assumption that the scenes remain static [22]. The depth estimates are used around object boundaries by operating on individual light rays [15]. When the ray space is sampled densely enough, each scene point appears as a line segment in such an epipolar-plane image (EPI) with the slope of the line segment depending on the scene point's depth. We can accurately estimate the slope of line segments or, equivalently, the depth of scene points. The slope m of a line segment associated with a scene point at distance z is given by

$$m = \frac{1}{d} = \frac{z}{f\,b} \tag{3.3}$$

where d is the image space disparity defined for a pair of images captured at adjacent positions or, equivalently, the displacement between two adjacent horizontal lines in an EPI, f is the camera focal length in pixels and b is the metric distance between each adjacent pair of imaging positions.

To compute depth estimates, a depth z, or equivalently a disparity d, are assigned to each EPI-pixel $(u, \hat{s})$. For a hypothetical disparity d the set R of radiances or colors of these EPI-pixels is sampled as

$$R(u, d) = \{E(u + (\hat{s} - s)d, s) | s = 1, \ldots, n\}, \tag{3.4}$$

where n corresponds to the number of views in the light field. From the density of radiance values in $R(u, d)$ a depth score $S(u, d)$ is computed in linearized RGB color space. The initial depth score [8] as

$$S(u, d) = \frac{1}{|R(u, d)|} \sum_{r \in R(u,d)} K(r - \bar{r}), \tag{3.5}$$

where $\bar{r} = E(u, \hat{s})$ is the radiance value at the currently processed EPI-pixel, and the kernel

$K(x) = 1 - \|x/h\|^2$ if $\|x/h\| \leq 1$ and 0 otherwise.

For each EPI-pixel$(u, \hat{s})$, the pixel's depth estimate is

$$D(u, \hat{s}) = \arg\max_{d} S(u, d). \tag{3.6}$$

3.3. Processing Data

The system continually learns from environmental data by supervised learning [26] to determine the abnormal scene. For example, the reconstructed building is not in a vertical position. It indicates the person wearing WOM is deviated from a straight position. The person may incline the body, fall or lean on an object. The task of supervised learning is:

Given a training set of N example input–output pairs $(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)$, where each y_i was generated by an unknown function $y = f(x)$, discover a function h that approximates the true function f.

Here x and y can be any value. The function h is a hypothesis. Learning is a search through the space of possible hypotheses for the one that will perform well, even on new examples beyond the training set. Supervised learning can be done by choosing the hypothesis $h*$ that is most probable given the data:

$$h^* = \arg\max_{h \in H} P(h|data). \tag{3.7}$$

$P(Y|x)$ is a conditional probability distribution.

The system processes the data from surrounding environments, and the health data from the person wearing WOM. Fig. 2 is a neural network which analyzes data to make the decision for the output.

3.4. Scene Rendering

The system 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 system automatically searches for a good point of view, allowing a good understanding of a scene for a human user[21]. The position will be the optimal light source position. Heuristic search is used to choose viewpoints only in potentially interesting regions, obtained by subdivision of spherical triangles.

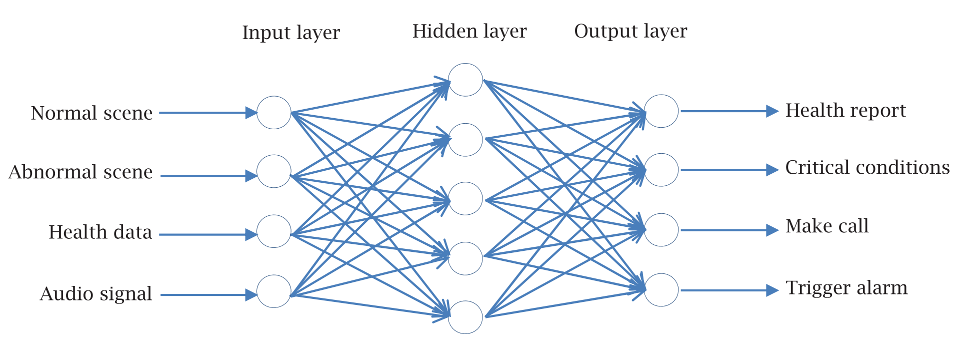

Fig. 2: A neural network for making decisions.

The points of view are supposed to be on the surface of a virtual sphere. The scene is in the center of the sphere. The surface of the sphere of points of view is divided into 8 spherical triangles (Fig. 3). The best spherical triangle is determined by positioning the camera at each intersection point of the three main axes with the sphere and computing its importance as a point of view. The three intersection points with the best evaluation are selected. These three points on the sphere determine a spherical triangle, selected as the best one. Fig. 4 shows an initial spherical triangle ABC, a new spherical triangle ADE is computed and so on. The vertices of spherical triangles represent points of view.

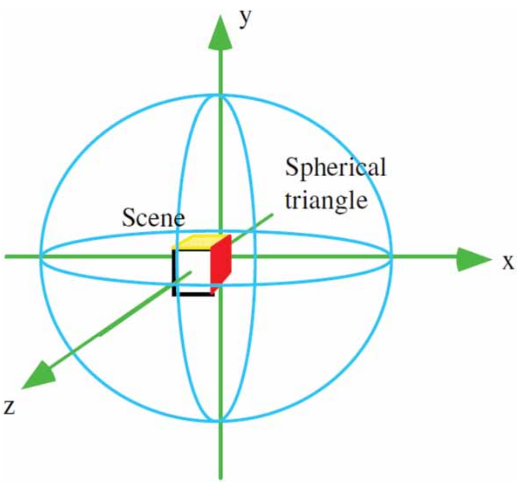

Fig. 3: Sphere divided in 8 spherical triangles.

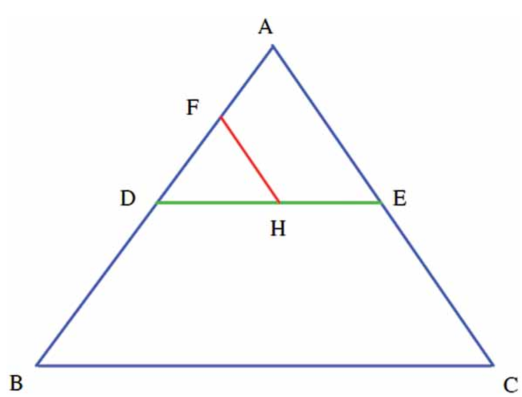

Fig. 4: Heuristic search of the best point of view by subdivision of a spherical triangle.

The importance of a point of view will be computed using the following formula:

$$I(V) = \frac{\sum_{i=1}^{n} \left\lceil \frac{P_i(V)}{P_i(V)+1} \right\rceil}{n} + \frac{\sum_{i=1}^{n} P_i(V)}{r} \qquad (3.8)$$

where, $I(V)$ is the importance of the view point V, $P_i(V)$ is the projected visible area of the polygon number i obtained from the point of view V, r is the total projected area, and n is the total number of polygons of the scene. In this formula, [a] denotes the smallest integer, greater than or equal to a, for any a.

A dynamic scheduling algorithm in the client side is used to optimize the loading and real-time rendering performance for the 3D scenes. The method can dynamically load and unload the partitioned data blocks from the server side [35]. Blocks are used for rendering according to the viewpoint parameters. With the change of the viewpoint, the rendering can be real-time scheduled in coordination with the internal and external memories. If the blocks in memory deviate from the viewpoint more than a predefined threshold, they are unloaded.

Assume that the rotation angle of the current viewpoint in the XZ plane is α, which will be quantized into one of the eight normalization angles. Suppose that the unload threshold of the scene blocks is:

$$TX(/TZ) = X_{nub}(/Z_{nub}) + 2\mathrm{sgn}(\cos(\pi + \alpha) \qquad (3.9)$$

where TX and TZ are respectively the scene blocks' index numbers along the X and Z axis. (X_{nub}, Z_{nub}) is the current viewpoint position.

To generate a 3D character model and render action of model in the scene is based on the idea of declarative modeling [2],[3],[24],[25]. Declarative modeling is a recent and emergent paradigm in the world of computer-aided design systems. As opposed to the imperative geometric modeling, it requires neither a complete knowledge of the final result at start time nor specified numeric details. Furthermore, consistency of the description can be automatically and continuously maintained by the system [25].

The character structure of our system is shown in Fig. 5. The character is generated by the system through the following stages:

1. The designer - the person wearing WOM provides a description, for example, I am walking.
2. The current description is translated into a description language – to allow interaction between the modeler and the designer.

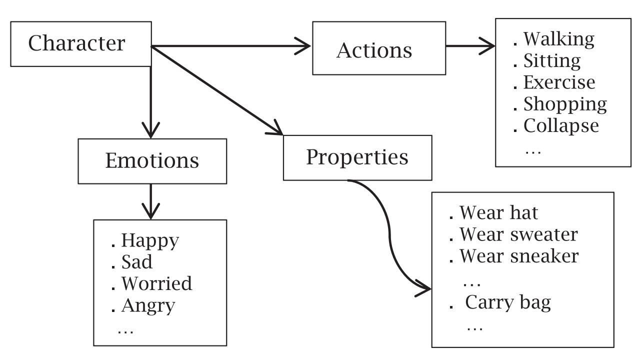

Fig. 5: The character structure.

3. From the description language the system produces a model.

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 own 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 information, fall detection, and health data as auxiliary information. As long as the person is wearing WOM, it is all 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.

ACKNOWLEDGMENT

This work is supported by National Science Foundation of China (61020106001, 61170324), National Science Council of ROC (NSC-100-2811-E-007-021), and a joint grant of National Tsinghua University and Chang-Gung Memorial Hospital (101N2756E1).

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