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A Real-time System for In-home Activity Monitoring of Elders

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***Abstract*—In this paper, we propose a real-time system for in-home activity monitoring and functional assessment for elder care. We describe the development of the whole system**

analyzed and visualized into graphs from which eldercare professionals are able to understand massive video monitoring data within a short period of time. Our experimental results demonstrate that the proposed system is efficient in indoor elder activities monitoring and easily utilized by eldercare professionals.

I. Introduction

Nowadays, aging population shows a dramatic increasing during the past decade, which is not limited to the United States. There will be an aging population explosion in many other countries as well. Therefore, independent lifestyles are highly desired by elderly people. But independent lifestyles of older adults often come with high risks. Many smart home technologies implemented with various sensors have been developed to track and monitor activities of elderly persons at home and assist their independent living [1].

In this work, we propose to explore a real time system for video-based activity monitoring and functional assessment for eldercare. Figure 1 provides an overview of the proposed system. The video sensor, coupled with intelligent computer vision and learning algorithms [2], provides rich and unique information that cannot be obtained from other types of sensors. We embed a video system in the living environment of elders and continuously monitor their activities at home. Silhouettes are extracted for privacy protection, and silhouette features are summarized and visualized to assist eldercare professionals understanding of massive video monitoring data within a short period of time. The data collected by our proposed system demonstrates its efficiency.

The rest of the paper is organized as follows. The detailed system designs are described in Section 2. Section 3 explains the silhouettes extraction algorithm. Section 4 summarizes the feature extraction and visualization algorithms. Experimental results are presented in Section 4. Section 5 concludes the paper.

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II. Real-time System Design

In this section, we introduce our system design and

privacy are important requirements of any video-based activity monitoring system to be deployed in the home. For unobtrusiveness, the cameras need to be invisibly embedded and the whole system should be compatible to the living environment.

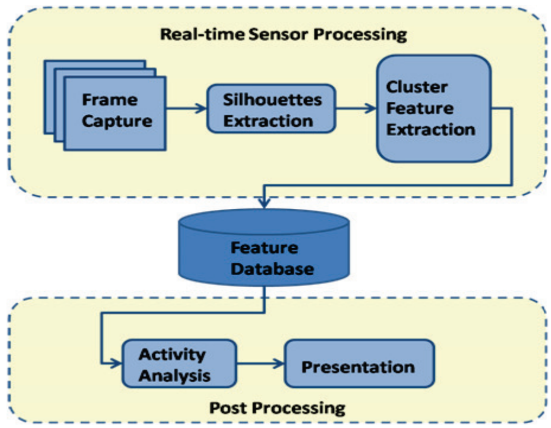


Figure 1: Overview of the proposed system.

In this work, we develop a friendly looking Elder Care system as shown in Figure 2. It has the following major components: a Unibrain fisheye camera for frame capture which has a viewing angle of 180°, a lamp of 6 feet height with mounted camera, a micro-computer for image processing and data storage which has a 1.50 GHz Intel Celeron CPU and a 80 GB hard disk drive. The computer is housed in a single drawer of an attractive end table which is approximately 2 feet high.

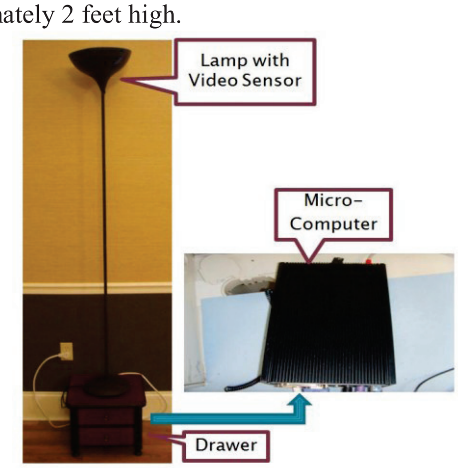


Figure 2: Configuration of our Elder Care system, the micro computer is put in the drawer when collecting data.

Figure 3 shows the video-base activity monitoring system parts. As seen in the pictures, there is no noticeable difference between a regular lamp and the system. We attach the lamp on the top of the drawer when collecting data, so the camera is about 8 feet from floor.

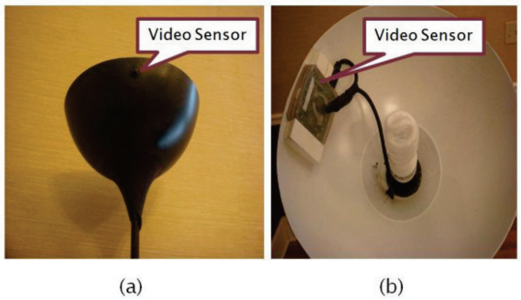


Figure 3: The appearance of the video sensor deployed in the lamp. (a) The front view of video sensor with lamp (b) The top view of the video sensor with lamp.

Figure 4 shows a living room picture captured by the system in a typical location. From the picture we can see almost the entire layout of the room including the apartment door entry, the whole kitchen area, the door of laundry closet, the door to bedroom and the whole living room area. In all, we collected more than 100 hours of frames of different residents for testing out system.

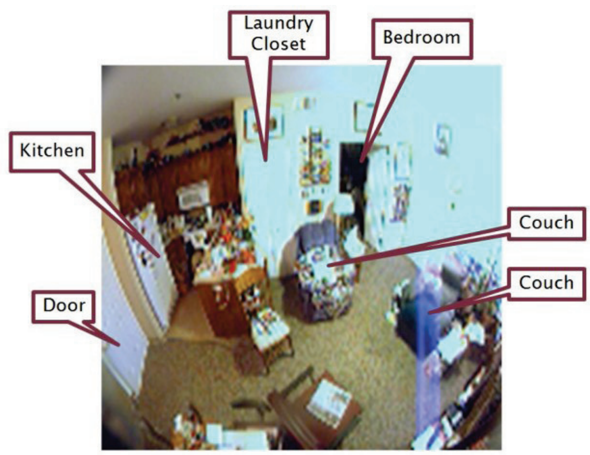


Figure 4: Picture captured using the fisheye camera installed in a living room of a one-bedroom apartment.

III. SILHOUETTE EXTRACTION

In this work, silhouette extraction serves two major purposes. The first one is privacy protection. After extracting the human form from the background, we fill the corresponding image region with black pixels so as to block identifying features. Our recent focus groups with elderly people at TigerPlace, an independent living facility at Columbia MO, show that video monitoring with silhouette extraction in the living room and kitchen areas is generally acceptable to elderly people [3]. Second, after silhouette extraction, we track human movements over time and extract important spatiotemporal features for automated activity analysis. For these purposes, silhouette extraction must be real-time and accurate.

Accurate and robust silhouette extraction in an indoor living environment is a challenging task because of time-varying light conditions, strong shadow, and dynamic background changes. Changes in lighting conditions can be caused by changing sunlight, indoor lights being turned on and off etc. These changes pose a significant challenge to the building of a stable silhouette extraction background model.

Another important challenge is dynamic background changes caused by human activities in the home. For example, chairs, cups, or books are frequently moved by the person. For accurate silhouette extraction, we need to update the background model to incorporate these changes. However, frequent background update is also risky. For example, if a person sits or sleeps on a couch for a long time, say 10 minutes, the algorithm may consider the person as a static object and "absorb" it into the background. In this case, we need to resort to high-level knowledge, such as human tracking, to assist the background update in an adaptive fashion.

For our Elder Care system, we use the silhouette extraction algorithm developed in [4] which is effective and accurate. Silhouette extraction is considered as an adaptive classification problem. High-level knowledge is fused with low-level feature-based classification results to handle time-varying backgrounds changes in lighting conditions. Brightness and chromaticity distortion are used to detect and remove shadows. Figure 5 shows the scheme used for our silhouette extraction.

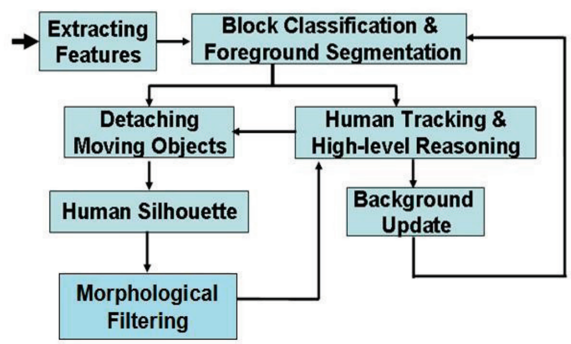


Figure 5: the proposed scheme for silhouette extraction.

In silhouette extraction within a dynamic video scene, we need to continuously update the background model by incorporating background changes. A commonly used method to update background is that, if an object or image area remains stationary for a certain period of time, it is considered to be background. In our work, we use the past Δ frames to update the background model. Therefore, any object that remains stationary over Δ frames will be incorporated into the background. For accurate silhouette extraction, we propose to utilize high-level knowledge about human motion as a guideline to perform adaptive update of the background model. The image blocks which contain the human body are updated very slowly so that the human body is not updated as background. Those blocks outside the predicted body region can be updated much faster to make sure that new objects are quickly incorporated into the background.

For this system real-time performance is a key algorithm driver. We achieve a processing rate of 7.0 frames per second on a fan-less 1.5GHz PC. Table 1 compares the performance of our silhouette extraction algorithm with that in [5]. It can be seen that our algorithm achieves a significantly smaller error rate than the algorithm in [5].

TABLE I
Average error rates on test video sequences

Algorithms	Average Error Rate
Algorithm in [5]	12.1%
Our Algorithm	7.3%

IV. ACTIVITY ANALYSIS IN AN INDOOR ENVIRONMENT

In continuous video monitoring of elders' activities at home, the data will be massive. Therefore, we need to develop a scheme to summarize the important activity information extracted from massive video data and present it to eldercare professionals in an effective manner.

The objective of automated activity analysis is to convert visual input data in the form of a stream of human silhouettes into meaningful information. In our work, we generally estimate the moving speed, which is an important feature for recognizing human actions, such as standing, walking, etc. Furthermore, it is a critical variable in assessing physical functions, activity levels, and energy expenditure of elderly people at home.

According to our experience, the centroid (1) is a very effective feature for representing the silhouette position.

$$x_i = \frac{1}{N}\sum_{j=1}^{N} x_{ij} \qquad\qquad y_i = \frac{1}{N}\sum_{j=1}^{N} y_{ij} \qquad (1)$$

where N is the total number of silhouette pixels, x_{ij} and y_{ij} represents the pixel location in the original image.

We denote $p(x_i, y_i)$ as the centroid position of the silhouette in frame i. We exploit the past Δl frames to compute the average distance $\bar{d}$ between silhouettes in each two consequent frames using equation (2). Since the frame capture rate is 7.0, we set $\Delta l = 7$, then v (3)is the estimated moving speed.

$$\bar{d} = \frac{1}{\Delta l}\sum_{i=1}^{\Delta l} \left\| p_i - p_{i-1} \right\|^2$$
$$= \frac{1}{\Delta l}\sum_{i=1}^{\Delta l} \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2} \qquad (2)$$

$$v = \sum_{i=1}^{\Delta l} \bar{d} \qquad (3)$$

Our current system focuses on location and moving speed. In our next step of research, we shall also develop advanced data mining algorithm to explore more activity patterns in the massive activity data and link them with medical records for automated functional assessment and early identification of potential health problems.

V. RESULTS

Three example image sequences showing the performance of the silhouette extraction algorithm are shown in Figure 6, Figure 7 and Figure 8. Note that the segmentation algorithm effectively segments the human from the background.

Figure 9, Figure 10 and Figure 11 are the location and action level plots corresponding to the Figures 6-8 respectively. Figure 12 shows the distribution of major actions of one person.

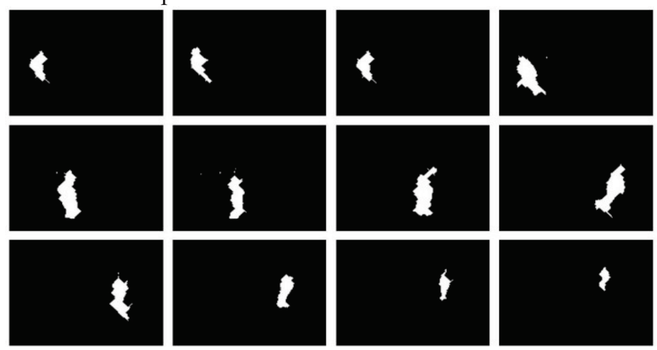


Figure 6: Silhouettes of person walking from kitchen to bedroom

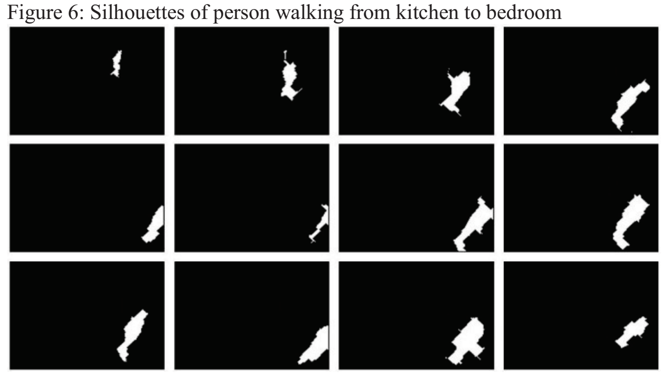


Figure 7: Silhouettes of person walking from bedroom to couch

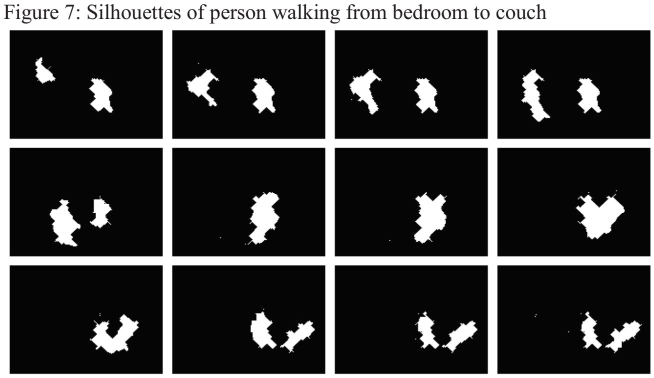
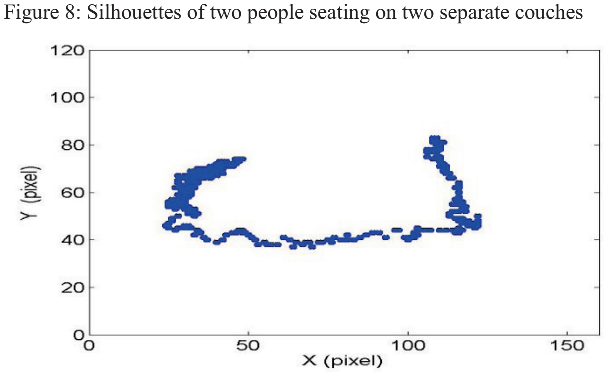
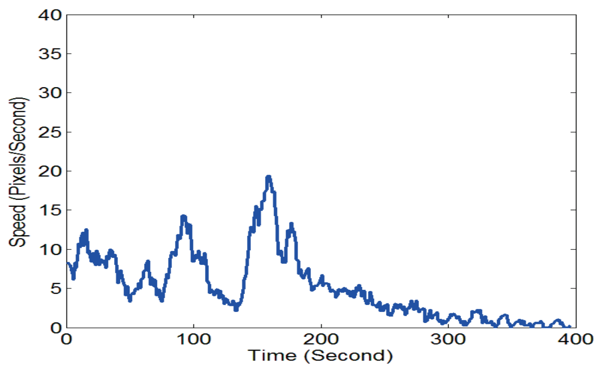


Figure 8: Silhouettes of two people seating on two separate couches

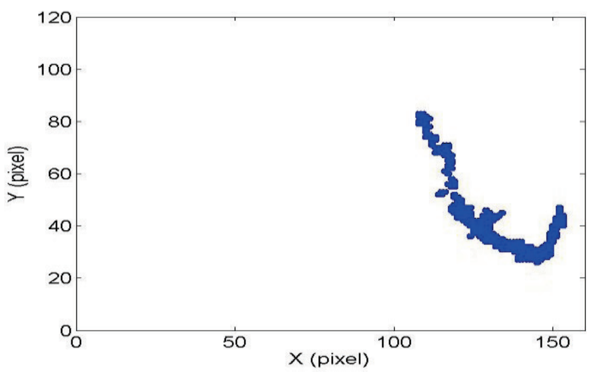


(a)

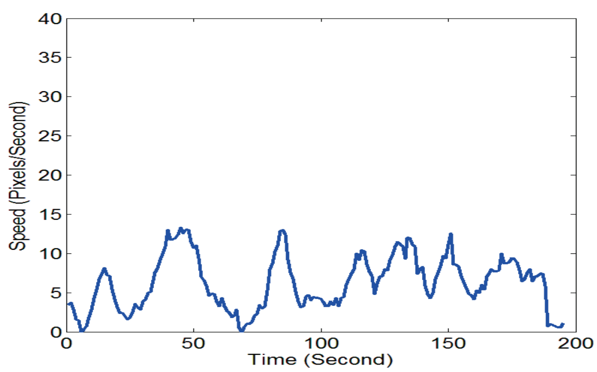


(b)

Figure 9: Location and speed estimation for 1 person with high activity, as shown in Figure 6. (a) Locations of silhouettes (b) Estimated moving speed of silhouettes.

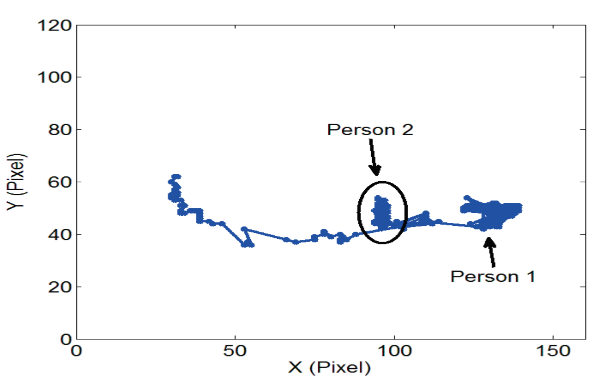


(a)

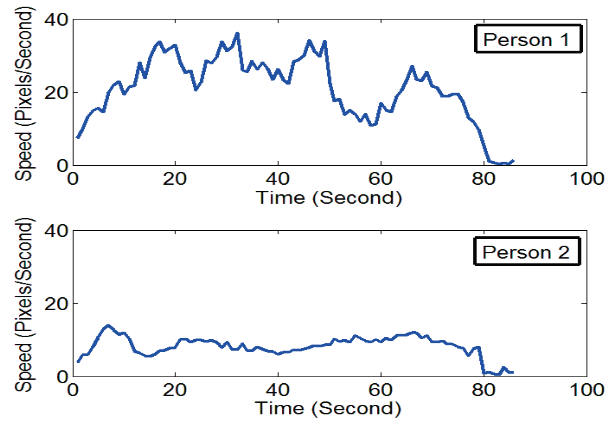


(b)

Figure 10: Location and speed estimation for 1 person with high activity, as shown in Figure 7. (a) Locations of silhouettes (b) Estimated moving speed of silhouettes.



(a)



(b)

Figure 11: Location and speed estimation for 2 people with different moving speed. (a) Locations of silhouettes (b) Estimated moving speed of silhouettes

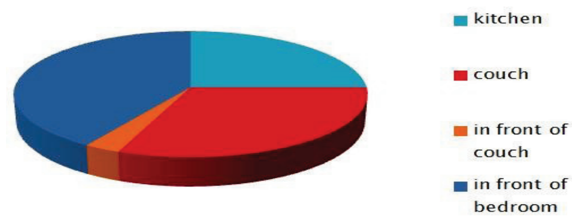


Figure 12: Distribution of major actions of one person with a ten minutes period.

VI. Conclusion

In this paper, we propose a real time system for elder care. We describe the development of the whole system which is able to efficiently extract silhouette. We then further analyze the collected silhouette features. Our experimental data demonstrate that the proposed system is efficient and the silhouettes are accurate.

Acknowledgment

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