FROM IMAGING NETWORKS TO BEHAVIOR PROFILING: UBIQUITOUS SENSING FOR MANAGED HOMECARE OF THE ELDERLY

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Abstract

*With demographic changes of the aging population and the increasing number of people living alone, pervasive home monitoring is set to play an important role in maintaining the independence and improving the quality of life for the elderly. The UbiSense† project aims to establish smart sensing networks based on low cost embedded video platforms for movement tracking and gait, posture analysis. To ensure privacy, the captured images in UbiSense are immediately filtered at the device level into blobs, which only encapsulate the shape and motion vectors of the subject so that no visual appearance of the subject is ever used. This demonstration will outline the concept of "**from blob to personal metrics to behaviour profiling**", and illustrate the latest hardware platform and software implementation of the UbiSense design.*

1. Introduction

Increasing demand on public healthcare service due to the aging population has become a major problem in developed countries. In parallel with the advances in ubiquitous computing techniques, extensive research is being carried out in using sensor networks for home care environments [4]. Existing research has shown that with the use of simple contact sensors combined with RFID, basic behaviour profiling can be achieved for the care of the elderly. However, the general lack of richer movement information means that precursors to certain adverse events cannot be detected.

For many years, clinical gait analysis studies have shown that changes in posture and gait, especially of the elderly or patients with chronic illness, can provide telltale signs of the onset of an adverse event or the deterioration of an existing problem [3,6]. In contrast to sensor based homecare systems, extensive research has been conducted to investigate the use of computer vision techniques and low cost video based systems for monitoring and assessing daily activities of the occupants. For example, Brumitt *et al.* proposed a vision based activity monitoring system which can be used for homecare applications [1], Nait-Charif *et al.* presented a simple vision system in a supportive home environment for activity recognition and fall detection [5], and Gao *et al.* proposed a technique of fusing motion segmentation with tracking for eating behaviour analysis of patients in a nursing home [2]. With the increasing number of elderly replying on homecare, better monitoring and analysis systems are crucial for maintaining and improving the quality of life for the elderly.

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2. UbiSense

The UbiSense project aims to develop an unobtrusive health monitoring system for the elderly. It differs from existing approaches by using embedded smart vision techniques to detect changes in posture, gait and activities. In addition to monitoring normal daily activities and detecting potential adverse events such as falls, the UbiSense system aims to capture signs of deterioration of the patients by analysing subtle changes in posture and gait. In the case of Parkerson's disease, for example, this can be the shuffling signs and other related behaviours. One of the major challenges of vision-based systems is the apparent intrusion of privacy due to the way that image data is transmitted and analyzed. To circumvent this problem, the captured images in UbiSense are immediately filtered at the device level into blobs, which only encapsulate the shape outline and motion vectors of the subject. Visual images are not stored or transmitted at any stage of the process so that it is impossible to reconstruct the abstract information back into an image showing the visual appearance of the subject.

To analyze the activity of the subject, the position, gait, posture and movement of the blobs in the image sequences are tracked, and this subject-specific information is called "*personal metrics*". These personal metrics can be transmitted between sensors so that complex behaviour profiling can be performed by utilizing resources of other UbiSense nodes in the network. The basic goal of UbiSense is to measure variables from individuals during their daily activities in order to capture deviations of gait, activity and posture to facilitate timely intervention or provide automatic alert in emergency cases. Considering the fact that behaviour profiling involves a set of highly demanding computational tasks that typically require expensive hardware and sophisticated setup procedure, the UbiSense project investigates the use of a networked low cost embedded smart video sensors to provide complex behaviour profiling functions based on resource scavenging, dynamic clustering and self-configurations.

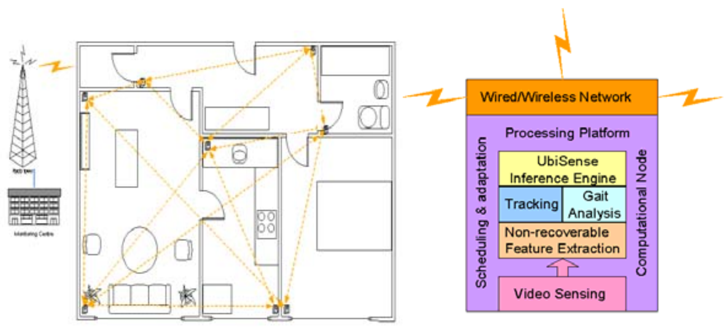

Fig. 1. A schematic diagram of UbiSense in a home environment (*left*), and the architectural design of an UbiSense node (*right*)

2. System Design and Demonstration

Fig. 1 schematically illustrates a typical home environment setup of the UbiSense platform and the corresponding architectural design of the smart sensing node. Each UbiSense node consists of an embedded smart camera VCSBC50 (a DSP camera with the ADSP 2185), a wireless link provided by an integrated BSN node, and a battery, as shown in Fig.2. The BSN node is a miniaturized (26mm) generic wireless sensing platform for context aware sensing environments. The BSN node uses Texas Instrument (TI) MSP430 16-bit ultra low power RISC processor with 60KB+256B Flash memory, 2KB RAM, 12-bit ADC and 6 analog channels (connecting up to 6 sensors). The wireless module has a throughput of 250kbps with a range over 50m. In addition, 512KB serial flash memory is incorporated in the BSN node for data storage or buffering. The BSN node runs TinyOS and can provide a seamless integration of ambient and on body sensing requirements. With its compact design (10x7x6cm), the UbiSense node can be installed easily by the user.

Fig. 2. A prototype UbiSense node.

One of the main objectives of the UbiSense project is to develop efficient posture and activity analysis algorithms based on fusing multiple visual cues from the shape and motion of the blobs. Fig. 3 gives an example of posture estimation and activity prediction of the current UbiSense implementation. The posture is estimated by fusing multiple cues, such as projection histogram and elliptical fitting, obtained from the blobs and comparing with reference patterns as shown in Fig.3 (*bottom*). The histogram is defined as the total numbers of pixels in the blobs projected along horizontal or vertical directions, and ellipse fitting is obtained based on applying moment operators onto the blobs. An ellipse is defined in a 5D parameter space as $[\bar{x},\bar{y},\phi,a,b]$, where $(\bar{x},\bar{y})$ is the central position of the ellipse. The orientation, ϕ, is defined as the angle of axis of the least moment of inertia, and it can be computed by the central moments.

$$u_{pq} = \sum_x \sum_y (x-\bar{x})^p (y-\bar{y})^q f(x,y)$$

$$\phi = \frac{1}{2} tan^{-1}\left(\frac{2u_{11}}{u_{20}-u_{02}}\right)$$

From the posture estimation results, activity can be accurately determined (*e.g.,* from sitting, standing, falling down, to standing and sitting again in Fig. 3 (*top*)), and no explicit tracking is required. Unlike previous gait classification studies and gait-based human identification, the method not only determines different types of the same walking gaits but also decides whether it is deviated from usual walking pattern. Experimental results on a simulated dataset show an average accuracy of above 90% in identifying different postures.

The proposed demonstration will illustrate the latest design of the UbiSense system and outline the potential of smart vision systems for pervasive homecare. We will outline the concept of "*from blob to personal metrics to behaviour profiling*" and illustrate our strategy used for ensuring privacy and security. The demonstration will also provide information on how to integrate the UbiSense platform with other sensing platforms such as the BSN nodes. Live demonstration on activity tracking, autonomic sensing and self-reconfiguration will be provided. Furthermore, we will also illustrate how the derived subject specific information, or personal metrics, can then be used to deduce behaviour profiles for abnormality detection. Combined with environment recognition, sensor fusion and distributed processing techniques, UbiSense has a great potential to become an integral part of intelligent homecare monitoring in the future.

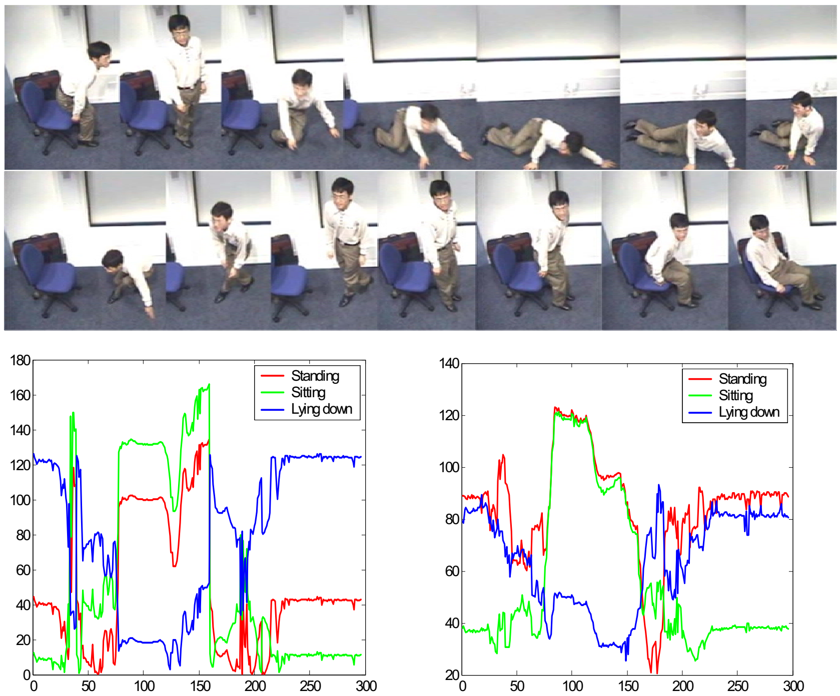

Fig. 3. Posture estimation and activity reasoning. Example images of the simulated activities where the subject changes his posture from sitting to falling onto the ground, and from lying on the ground back to sitting (*top*) and results of posture determination using elliptical fitting and projection histogram (*bottom*)

3. References

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