Self-Configuring Video-Sensor Networks

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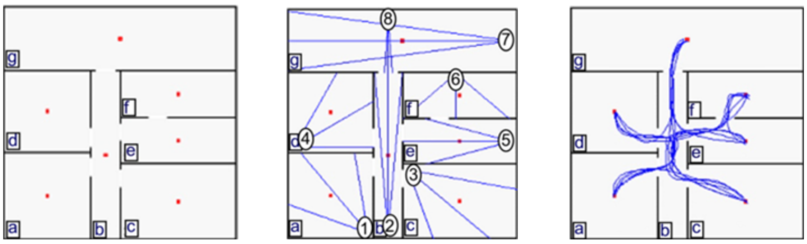
Abstract. A growing demand on healthcare providers worldwide is the provision of long-term care for the elderly. Instead of relying on nursing homes, a better way to maintain and improve their well being is to provide managed care in their own dwellings. The use of video based sensing provides an effective means of detecting changes in activity, gait and posture but the installation and calibration of the sensors are major obstacles to overcome in practical applications. This paper presents a novel MDS (Multidimensional Scaling) based self-configuration technique for video sensor networks. It allows implicit estimation of the geometrical locations of the sensors and permits the optimal usage of resources under a distributed processing environment.

1 Introduction

In almost all countries, longevity has given rise to expensive age-related disabilities and diseases. With the steady decline of the ratio of workers to retirees, a fundamental change of the way that we care for the aging population is required. Older adults of 65 and above already constitute one-fifth of the total population, and it is expected this will continue to grow. With the maturity of sensing and pervasive computing techniques, extensive research is being carried out in using sensor networks for home care environments. Extensive research is now directed towards the use of sensor networks for promoting healthy behaviours, early disease detection, improved treatment compliance, and support for informal care giving. These personal wellness systems are not meant to replace hospital, clinics, and physicians but rather to put the activities of daily living more into the healthcare mix. For the elderly, home-based healthcare encourages the maintenance of physical fitness, social activity and cognitive engagement to function independently in their own homes. Existing research has shown that when privacy and security issues are properly addressed, video based sensor networks provide an effective means of monitoring behaviour changes. For example, the UbiSense system allows the captured image immediately turning into blobs at the device level that encapsulate shape outline and motion vectors of the body. No visual images are stored or transmitted at any stage of the processing. Furthermore, it is not possible to reconstruct this abstracted information into images. One of the major challenges of the video based system is the complexity of site installation and calibration on relative physical orientations and locations of the sensors, which are important for activity tracking and inferring abnormal behaviours. The purpose of this paper is to propose a novel self-configuration method based on multi-dimensional scaling (MDS) for estimating the spatial positions of the sensors. The proposed technique relies solely on the movements/activities captured by the sensors and no explicit calibration/configuration process is required at any stage, thus significantly simplifies the deployment process. In addition, by the use of Markov modelling, the proposed technique can be used for computational resource scavenging, allowing distributed processing with low-cost vision devices for performing complex processing tasks.

2 Self-Configuring Network

The proposed method is based on implicit self-calibration. Once all the sensors are installed, the general movement of the occupant is tracked and the relative camera activation pattern is derived. Based on the activation pattern, the relative spatial distance between the cameras can be estimated accordingly. To facilitate the development of the self-configuration algorithm, a simulated care home environment is designed as shown in Fig. 1(a) where the centroid of each room is highlighted. In this case, we assume that each room has a camera, and a camera at each end of the corridor. The cameras' respective field of view (FOV) is defined as in Fig. 1(b). Fig. 1(c) outlines simulated movement of the occupant, and from the relative activation of the sensors when he enters/leaves the FOV, we aim to work out the geometrical relationship of the cameras and rooms. It is important to note that no knowledge about the plan of the dwelling or camera location is required for the proposed self-configuration algorithm. Only the temporal activation pattern of the sensors is required during the configuration stage.



(a) (b) (c)

Fig. 1. A schematic illustration of a simulated care home. The architectural design of the house (a) where the centriod of each room is highlighted, the camera FOV (b), and the simulated walking patterns in the house (c).

To estimate the spatial correlation of the sensors based on the camera activation patterns, MDS was used. MDS is a technique for providing visual representation of the pattern of proximities among a set of objects [1]. It is an iterative non-linear technique for projecting data to a lower number of dimensions [2]. Denote the distance between each pair of sensors is $\vec{\Delta} = [\delta_{ij} : i, j = 1,..,n]$, MDS [3,4] identifies the configuration $\overrightarrow{X} = [x_{ia} : a = 1, ..., p]$ of n points in a p-dimensional space, such that point $\vec{x}_i = (x_i, ..., x_{ip})^T$ uniquely represents sensor i, and the Euclidean distance between $\vec{x}_i$ and $\vec{x}_j$: $d_{ij}(\overrightarrow{X}) = \left\| \vec{x}_i - \vec{x}_j \right\| = \sqrt{\sum_{a=1}^{p} \left(x_{ia} - x_{ja} \right)^2}$ approximates the corresponding distance δ_{ij} between sensor nodes, for all pairs of sensor nodes (i,j): $\forall_{i<j} d_{ij}(\overrightarrow{X}) \approx \delta_{ij}$. Fig. 2 demonstrates the MDS result in 3D and its projection to 2D along the two principal dimensions. It is evident that the general trend follows the true geometrical locations of the sensors. However, when there is significant overlap of the sensor FOV, their relative distance is difficult to separate. In addition to estimating the layout of the sensor nodes, the derived map can also be used as a guideline for resource sharing. As each camera node will have limited processing power, to provide computational intensive video-based gait/posture analysis, tasks will have to be distributed throughout the network. Since the camera nodes are spread around the entire building and only a few cameras may be active at any moment in time, these non-active camera nodes can be assigned to perform background processing tasks.

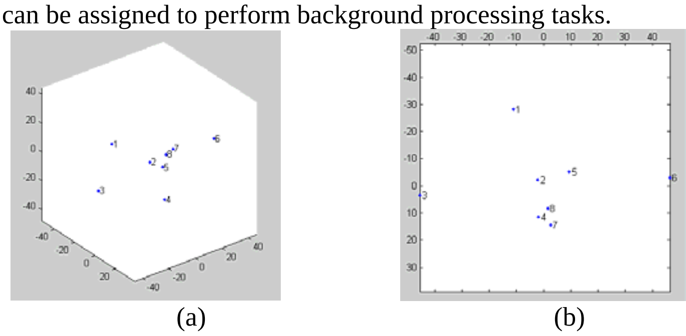


Fig. 2. The estimated spatial correlation between cameras in 3D (*a*) and 2D (*b*) spaces.

To predict the probability of which node may become active given the subject being within a particular sensor FOV, Markov transition matrices are derived. Fig. 3 shows the corresponding transitional probabilities of each camera with respect to others for the same simulation data used in Fig. 2.

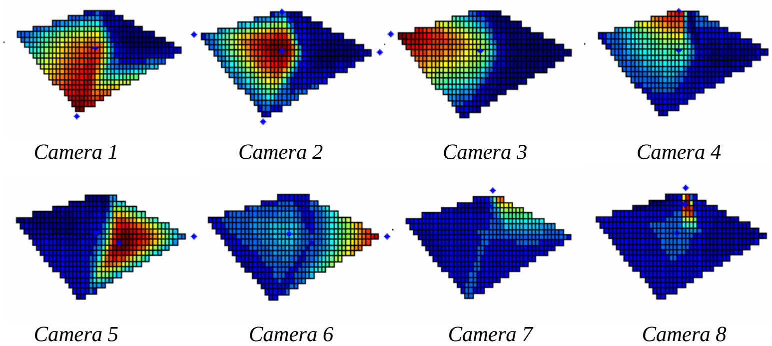


Fig. 3. Transitional probabilities of the eight cameras used in Fig. 1.

To validate the derived model, Fig. 4 illustrates the result of using the model to activate the camera node based on the subject's location where the small blue dot represents the subject, the red dots represents the camera node in each room, and the activated camera nodes are highlighted with a square.

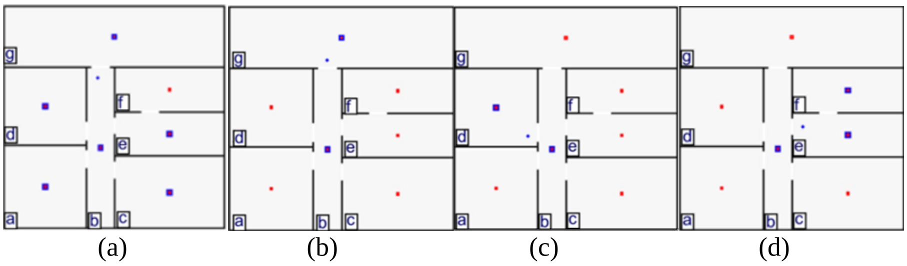


Fig. 4 Automatic camera activation based on the location of the subject where the small blue dot represents the location of the subject, the red dot represents the camera node in each room, and the blue squares highlights the active camera node.

4 Conclusions

This paper describes a self-configuration technique for video sensor network based on MDS. The proposed method relies only on the movement of the subject, and the relative spatial positions of the cameras are estimated according to the sensor activation patterns. The proposed technique also enables the detection of deviation to normal activity patterns and facilitates distributed processing by the incorporation of Markov modelling.

References

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