An Integrated Multi-Sensing Framework for Pervasive Healthcare Monitoring

Abstract — **Pervasive healthcare systems provide valuable solution for monitoring elderly wellbeing, quantifying and measuring post-operative patient recovery, and observing the development of neurodegenerative diseases such as Parkinson's. However, developing functional pervasive systems is a complex task that entails the creation of appropriate sensing platforms, integration of versatile technologies, utilization of elaborate data analysis techniques and making available supporting stream management infrastructures. This paper describes an integrated multi-sensing framework where the sensing platforms, data fusion and analysis algorithms and software architecture suitable for pervasive healthcare applications are presented. The potential value of the proposed framework for pervasive patient monitoring is demonstrated and results obtained from real research experiences described.**

Keywords-component: pervasive sensing, body sensor networks, vision sensor networks, activity recognition, data fusion, behaviour profiling, pattern mining, data visualisation

I. INTRODUCTION

Recent advances in pervasive systems offer significant potential for healthcare delivery in terms of versatility and cost-effectiveness. For instance, wearable body sensor networks [1] are used for measuring postoperative recovery for patients undergoing major elective minimal invasive surgery where early signs of post-operative complication can only be captured in a home environment since patients are usually discharged much more quickly compared to conventional surgery [2]. Pervasive systems also provide an appealing approach for monitoring the wellbeing of the elderly where the general trend of an increasingly ageing population has placed significant burdens on current healthcare systems. For this purpose, smart homes employing different sensors can monitor patient interaction with the surrounding environment [3]. Such pervasive healthcare environments encourage independent elderly living, the maintenance of physical fitness and observing social activity while alleviating workload of healthcare professionals. They can also aid in identifying transient behaviour abnormalities that may indicate major adverse events.

In practice, pervasive systems are only realizable by integrating multiple sensing modalities and existing research has shown that there is a complementary relationship between wearable and ambient, *i.e.* background, sensing paradigms. For instance, wearable sensing enables continuous and unobtrusive monitoring of patient motion and physiological parameters through a series of body-worn sensors and computers wirelessly linked to each other. They are usually based on accelerometers [4, 5], pulse oximeters (SpO_2) [5], ECG [6] and temperature sensors [4]. However, wearable sensors only provide limited body information and due to the lack of global reference, it can be difficult to use this data to deduce the context of the activities. For example, accelerometer can detect local motion, such as detecting sitting or lying down; however, it cannot tell if the subject is sitting on a chair or on the ground. It is also difficult to differentiate between low-impact sedate activities performed within the home due to the complexity in separating fine motor motion from the movement of the body as a whole. It is only by the use of ambient sensing that other essential information such as body postures and effective activity discrimination can be obtained.

Ambient sensing frameworks utilise large number of sensors that are ubiquitously placed in the environment such as video cameras [7, 8], infrared sensors, water flow and utility usage sensors, and pressure sensors mounted on furniture [9]. These systems can provide information about the location and activities of the subject within the environment and enable the detection of critical events such as falls. Nevertheless, pervasive systems based only on ambient sensors suffer from a number of limitations. For example, it is difficult to infer detailed changes in motion patterns or detect vital signs related to the onset or progression of chronic disorders. In addition, the need for having large training data to be used for inferring activities hinders the practical use of ambient sensing frameworks. Furthermore, the use of large number of ambient sensors incurs complex and expensive deployments and makes this approach impractical.

By integrating the strengths of ambient and wearable sensing it is possible to provide true pervasive systems that can be used to accurately infer subject condition based on activity and physiological parameters. Sensory data can be fused at signal, data, feature, or decision levels [10]. For instance, sensor signals can be combined by using simple hardware thresholds [5], whereas at the data level, pattern recognition methods such as Bayesian Networks [7], Hidden Markov Models (HMMs) [11] and Gaussian Mixture Models (GMMs) [12] are often used for data fusion. Due to the large volume of sensing data, dimensionality reduction techniques such as Manifold Embedding [13], Principal Component Analysis (PCA) and feature selection [1] are often applied prior to applying the actual activity classification procedure.

Another major challenge associated with pervasive systems deployment is the integration and interoperability of diverse set of system components including sensors, middleware, web services, databases as well as backend data mining and visualization tools for different user groups and with varying levels of security expectations. Additionally, the need to collect and operate on continuous sensor data streams introduces significant computational and storage loads that are exacerbated in case of a large number of users. Therefore, the development of efficient and scalable stream processing and management architecture is essential for pervasive system deployment. A number of light-weight software architectures for scalable data processing, transmission and storage have been recently introduced based on techniques such as wavelets, histograms, sketches, sub-sampling and synopsis data structures [14, 15]. These techniques optimize resource utilization and reduce memory usage, lower database access rate and enhance responsiveness for web clients.

This paper describes an integrated framework for pervasive systems used in intelligent healthcare delivery and patient monitoring applications. We describe individual framework components that correspond to different pervasive system phases from data acquisition platforms to stream management to fusion and analysis. We also present results of research experiments carried out while developing and applying the proposed framework.

II. System Architecture

The software architecture for the proposed pervasive healthcare framework is based on the push style [16] message broker model [17] which is used by many established industrial systems such as J2EE [18] and several research frameworks [19]. Fig. 1 illustrates a schematic diagram outlining framework phases and data workflow. Patient activity information, as well as data captured by ambient sensors, is streamed through authorised gateway devices to broker server(s) for logging and interface to databases. Further processing, data fusion and analysis for patient activity classification and behaviour profiling are carried out on dedicated servers or distributed among clusters. Brokers work as intermediary connectors that facilitate communication between heterogeneous and distributed system components for data acquisition, processing, storage and visualization. Based on an asynchronous messaging paradigm, system components can publish data under a topic and/or subscribe to a particular topic or a category of topics. The broker delivers data to registered subscribers. It also enables for querying data-generating components that provide metadata in schema-conformant XML. User interaction with the system is implemented through web services and different stakeholders connect to the system in order to retrieve stored information or carry out specific data processing algorithms. The loose coupling of heterogeneous framework components allows for flexible and scalable pervasive system architecture that facilitate monitoring and knowledge discovery. Moreover, the use of secure connectivity and sensing data abstractions, as will be described in next section, is essential for protecting patient privacy.

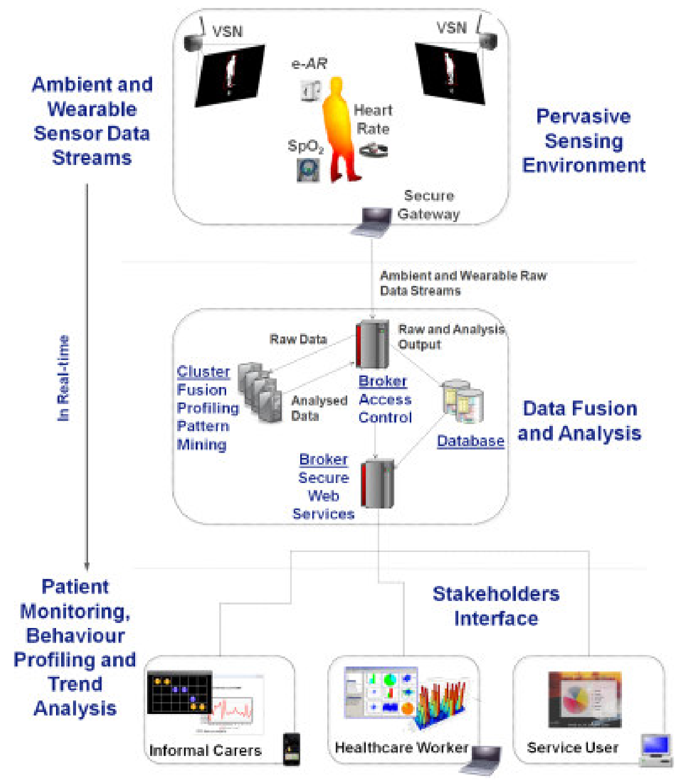

Figure 1. System architecture for pervasive monitoring applications where loose coupling between heterogeneous components enables for efficiency and scalability

III. Ambient and Wearable Sensing Platforms

A. *Vision-Based Blob Sensors*

The deployment of vision-based ambient sensors is based upon the concept of Visual Sensor Network (VSN). A VSN is a collaborative network of partly self-sufficient nodes. Such nodes, also referred to as "smart cameras" are usually composed at least of a camera, a processing unit and a communication interface. The main idea behind VSNs is to distribute the data processing across the boards as much as possible in order to reduce communications bandwidth and power consumption. For example, the Matrix Vision mvBlueLYNX smart camera has been demonstrated in the *SmartClassySurv* activity recognition framework [20]. This device embeds a vision sensor, a FPGA for pre-processing, a PowerPC processor, an ethernet interface for communication with the rest of the network and is powered through power over Ethernet (PoE).

For ambient sensing, we have developed a blob sensor that is a self-contained module consisting of a vision sensor, on-board processor, wireless communication and battery. It has a wall mount design and can be integrated into the home environment similar to a PIR security device. Video data observed by the device is processed on board in real-time and the sensor transmit only the derived signal metrics such as the silhouette, *i.e.* blob, of a moving object and its local motion in the form of optical flows. Through a network of blob sensors, accurate tracking can be achieved which can improve the overall system robustness in behaviour profiling. Typically, a blob sensor node is composed of:

- Omnivision OV9655 1.3 megapixel camera with interchangeable lenses and range of focal lengths (ultra wide angle 1.68mm to teleobjective 6.5mm)
- The main board embedding:
  - 500MHz Analog Devices Blackfin BF537 Processor (RISC MCU/DSP)
  - 256MB SDRAM, 32MB SPI Flash
  - Body Sensor Network (BSN) node connector
  - JTAG connector for debugging purposes
- Lantronix Matchport WLAN 802.11g/b Wi-Fi for wired/wireless comm. and Li-Polymer 3.7V-1A battery

The module dimensions are 50x45x45mm (not including the antenna) for a total weight of 80.5g (112g including the casing). Its total power consumption is 180mA in fully active mode. Fig. 2 shows an exploded view of the blob sensor hardware with annotated components.

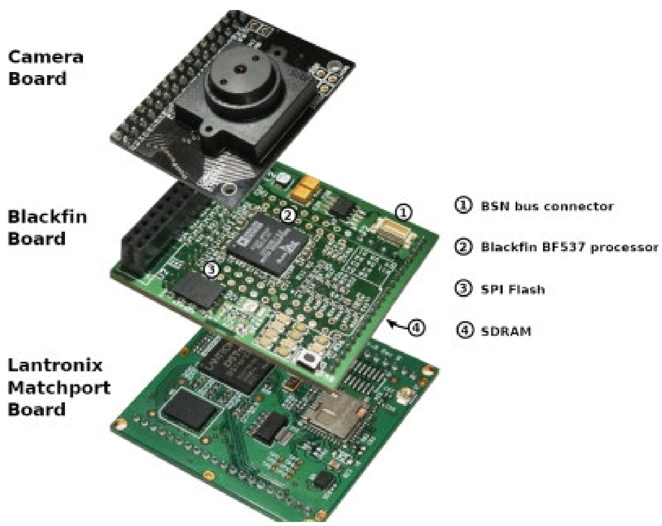

Figure 2. Visual sensor node components

Under this sensing paradigm, blobs representing the monitored subject are first extracted from the video signal using a background statistical model, where every pixel is represented as a Gaussian mixture distribution maintained over time [21]. Incoming signals are compared with the existing background model and segmented into a binary map of foreground and background. The Blackfin processing power is sufficient to enable on-node real-time background segmentation at a resolution of 320x256 pixels, using a single Gaussian for the background colour model. Using two or more Gaussians in a Gaussian Mixture Model (GMM) requires the use of floating point operations to fuse them, which is not supported in hardware by the current Blackfin processor. This would be too computationally expensive on this platform.

Further optimisations are necessary to reach a real-time system. The background model is only updated every 20 frames. A fast and low-resolution segmentation is performed beforehand to determine the region of interest (ROI). The full resolution segmentation and morphological filtering (erosion-dilation) are then performed only in the ROI bounding box, providing a substantial speed gain. A couple of basic features can be computed on node from the binary blob image, such as the blob centre, axis-aligned bounding box (AABB), and the eigenvectors of the blob, providing information on its orientation. In many situations, these features provide sufficient information. In such cases, only the features are transmitted through the network, reducing bandwidth usage and energy expenditure. It is worth noting that the silhouettes extracted by each ambient sensor do not carry any appearance information and no image data is transmitted to other devices. This is important for home care environments where privacy is of high priority. Fig. 3 illustrates captured scene images and computed blobs.

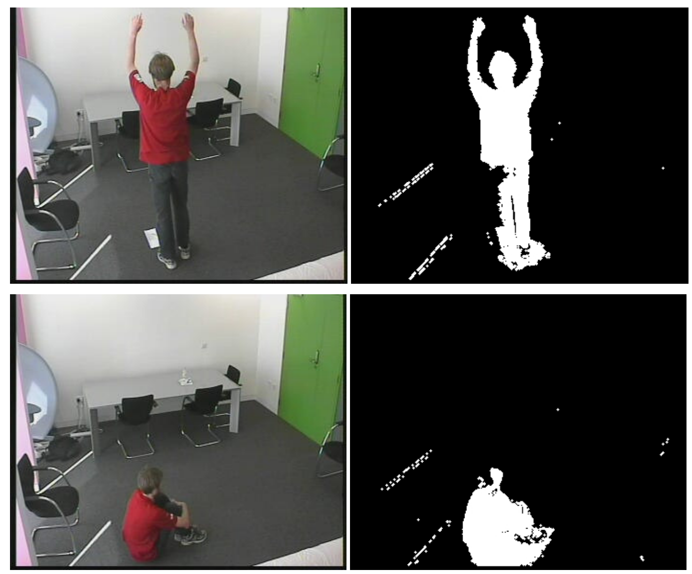

Figure 3. Scene images (left) and computed blobs (right)

B. *Ear Worn Activity Recognition (e-AR) Sensor*

Activity information and physiological patient parameters are acquired by using the ear worn Activity Recognition (*e-AR*) sensor [5] which is based on the Body Sensor Network (BSN) platform [22]. A basic BSN node comprises a Texas Instruments MSP430 16-bit ultra-low-power RISC processor, a Chipcon CC2420 radio transceiver, MCC ChipOX SpO_2 module, a temperature sensor and a 3-axis accelerometer. The BSN node runs TinyOS [23], which is a small, open-source and energy-efficient sensor board operating system. Fig. 3 shows the BSN node on a circuit board and *e-AR* sensor. During its use, the *e-AR* sensor periodically samples from the accelerometer and other sensors, and transmits this data to a nearby gateway station where motion features such as head-tilt, mean, median and variance are extracted to compute patient activity levels, *i.e.* activity indices. Alternatively, activity indices can be computed on BSN nodes in order to minimise transmission bandwidth, extend battery life and facilitate system scalability.

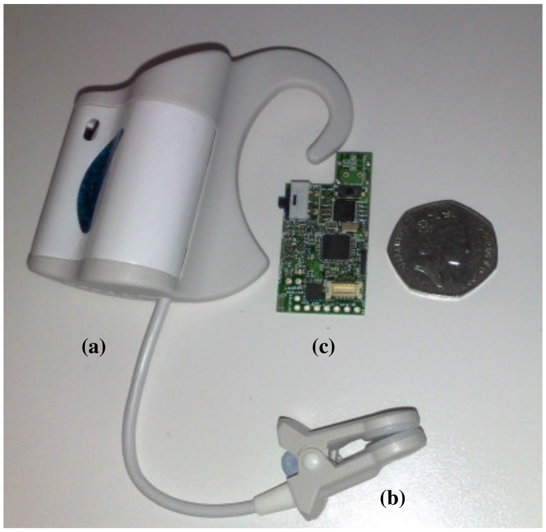

Figure 4. *e-AR* sensor (a) with SpO_2 reader cord that clips to the ear (b) and Body Sensor Network (BSN) node on a circuit board (c)

IV. DATA ANALYSIS

Data analysis is a vital stage in pervasive systems and is required for a very wide range of applications such as inference and learning for behaviour monitoring, context aware sensing where the settings and their impact on executed activities is studied, designing efficient databases that can encompass different types of sensor data and optimising queries to retrieve data from this database, and correcting for errors in data resulting from noise, interference and missing connections. Other important analysis applications include sensor fusion where different types of sensors are used to obtain better understanding of activity and pattern mining where patient activity is used to identify trends that occur over long period of time. The following subsections describe a number of data analysis techniques and their use in pervasive patient monitoring. Results obtained using these techniques within the proposed framework are presented in the next section.

A. *Gaussian Mixture Models and Probablistic Decision Level Sensor Data Fusion*

Through the fusion of ambient and wearable sensor information, it is possible to achieve increased accuracy in activity inference, enhanced tolerance to sensor failure through the inclusion of both complementary and redundant data types thus offering improved home monitoring systems with extended coverage of both local and global characteristics of activity. One approach for sensor fusion is by using a Gaussian Mixture Model (GMM) [12] which uses a Gaussian Bayes Expectation Maximisation (EM) classifier based on features extracted from wearable and blob sensors. For the *e-AR* these features include tilt and movement frequency spectrum whereas for the latter they include the aspect ratio and mean velocity of the blob. The classification considers that different activities correspond to different classes. It uses an EM iterative method to compute the maximum likelihood fit [24] based on the assumption that the conditional probability density function for each of these classes is Gaussian. The expectation and maximization steps are performed iteratively until convergence and part of input data is used to evaluate the accuracy of the classifier based on the marginal probability of every activity with the highest probability chosen for the final classification.

For environments housing multiple occupants, it is important to automatically identify related data streams before fusion may occur, a process known as sensor correlation. Probabilistic decision level fusion [25] is used for sensor correlation. In this case, feature sets are extracted such that they exhibit classification redundancy across sensing modalities. Consequently, activities can be detected accurately and independently by per-sensor classifiers at the same time. Feature set search space is firstly reduced by applying BFFS [1] to rank sensor-specific features which yield high accuracy when used singularly and independently. Subsequently, sets with the highest redundancy across sensors are automatically selected by using the multi-objective accuracy/redundancy score [26] to rank feature sets classification. With the appropriate e-*AR* and blob feature sets selected, they are exposed to pre-trained per-sensor activity classifiers. The results of these classifiers are then used to select those data streams that most likely result from the same subject. This technique enables automatic combination of ambient and wearable sensing data which improves overall activity classification for home healthcare monitoring.

B. *Behaviour Profiling Using Hidden MarkovModels (HMMs)*

Observing patient activity and movement patterns over extended periods of time can be cumbersome especially for large number of system users. A similarity based HMM technique [27] for clustering of location sequences, *i.e.* patient movement, can be used for representing the behaviour pattern of the patient and its temporal variation without explicitly defining activities, hence alleviating privacy concerns. Standard approaches to clustering with HMM comprise model training with a sequence, then using pair-wise distance based methods to perform the clustering. The proposed similarity based clustering approach uses a feature space that is generated using HMMs to express the similarity of sequences to each other. For this purpose, the features describing a sequence are calculated as similarity measures between that sequence and other reference sequences that are selected from the whole set as chosen by experts, or the whole dataset can be used. Patient behaviour profiling is achieved by observing the clustering of sequences in the new feature space. Assuming that certain clusters of behaviour sequences represent normal patient activity over a period of time, any outlier clusters can indicate deviations from normal behaviour patterns. If this deviation is large, further data analysis can be performed to study the causes and can result in patient contact for further investigation.

C. *Pattern Mining for Routine Behaviour Discovery*

Complementary to a model based approach for behaviour profiling is to discover patterns of activities using pattern mining algorithms. In [28] a system is proposed for constructing a compressed data structure specifically for describing routines by mining activity data patterns. Typically, when a user is wearing an e-*AR* sensor, an activity level is streamed from the sensor based on 4 seconds of data. The activity level is the output of a classifier described in [29], and can take one of four values where the lowest level indicates almost no activity (during sleeping or sitting) and the highest level indicates a high-intensity activity such as running. While some activities may be described by a single activity level, most activities result in a sequence of activity levels. These combinations are discovered by the pattern mining algorithm. The algorithm in [28] obtains a data structure called the routine tree, a picture of the user's routine showing patterns of activity at progressively finer time resolutions wherever there is more detail to uncover. Each node in the tree represents a time interval, for which frequent patterns are stored. A systematic, top-down tree construction method mines data at smaller durations, while avoiding mining in further detail where there is little further structure to discover. The tree is then pruned by merging adjacent time intervals that have the same maximal frequency pattern to produce a more compact representation. Generated activity tree provides a representation of the composition of a user's routine and combined with appropriate visualisation techniques, intuitive graphical views of behaviour patterns can be attained.

V. Results

The data sensing, management and analysis techniques described above were applied in patient monitoring experiments. For our studies we have designed a home healthcare laboratory where subjects can be observed performing a variety of tasks typically enacted within a living space. This laboratory has been augmented with support for both wearable and ambient 'blob' based vision sensors. By using e-*AR* and 'blob' sensors together we facilitate the extraction of local motion characteristics such as head tilt, sway as well as capturing overall pose and limb motion.

An initial study measuring the impact of fusing wearable and ambient sensing on the accuracy of activity classification has been carried out [12]. A set of 9 activities, shown in Table 1, were considered along with their recognition rates as illustrated in Fig. 5. For all activity classes, we note a marked improvement with the exception of sitting which displays a minor decrease. Gains are particularly marked for classes where *e-AR* sensor data is ambiguous due to a lack of global information, as in classes 2, 3, 5 and 6. What is seen is an increase in sensitivity of the aforementioned classes due to more discriminative data. Analysis of classification using *e-AR* alone would reveal that this increase in sensitivity is due to the correct classification of data items previously, and incorrectly, classified as 'Sitting' – thus whilst sitting has demonstrated a minor decrease to sensitivity, the specificity of this class has increased considerably. This validates our theory that extending sensor coverage to both local and global characteristics will result in more accurate activity classification.

TABLE I. THE SET OF 9 ACTIVITIES USED IN [12]

Activity	**Class**
walking	1
standing	2
standing (head tilted)	3
Sitting	4
Reading	5
Eating	6
Sitting(Sofa)	7
Lounging	8
Lying Down	9

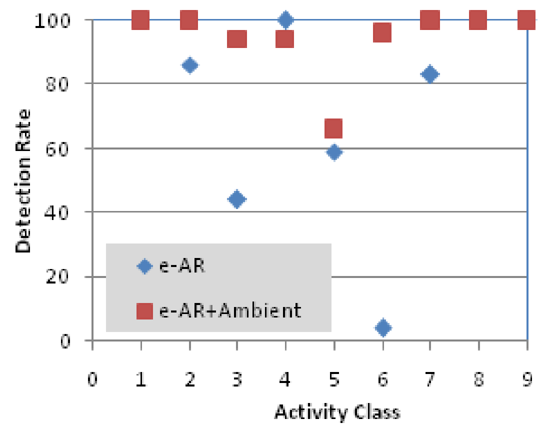

Figure 5. Activity recognition rates for 9 activity classes using the e-*AR* sensor alone and the e-*AR* sensor + blob sensor

In order for home monitoring systems to be readily adopted there is a requirement that they should address multiple occupancy scenarios with the minimum of user interaction. Given a choice of 'blobs' extracted from the environment along with a set of e-*AR* signals, the probabilistic decision level fusion technique proposed in [25] can automatically match the correct e-*AR* sensor to the 'blob' extracted from its wearer. This has important consequences for environments such as care-homes, where many patients may be under observation, requiring the correct signals to be matched before fusion can occur.

Figure 6 shows the results obtained when the probabilistic decision level fusion technique is applied to a scenario with three people in a room. For this experiment, one real subject, wearing an e-*AR* sensor and monitored by a blob sensor, is used along with two streams simulating random blob information for two other occupants. The scenario comprised a one minute activity of each of the following: sitting, reading, eating, standing, standing with head tilted, walking, sitting on sofa, slouching and lying. The three traces in Fig. 6 correspond to the percentage of time the e-*AR*/blob pairs were matched during the experiment. It can be seen that the proposed technique achieves a high degree of correlation accuracy matching e-*AR*/blob information for the real subject (blue trace) with low matching percentages for the randomly simulated blob information (yellow and purple traces). The activities returned from the blob and *e-AR* classifiers for the real subject are also presented at the top. It should be noted, however, that the technique is sensitive to the behaviour of the "erroneous" people in the room, *i.e.* people doing the same thing.

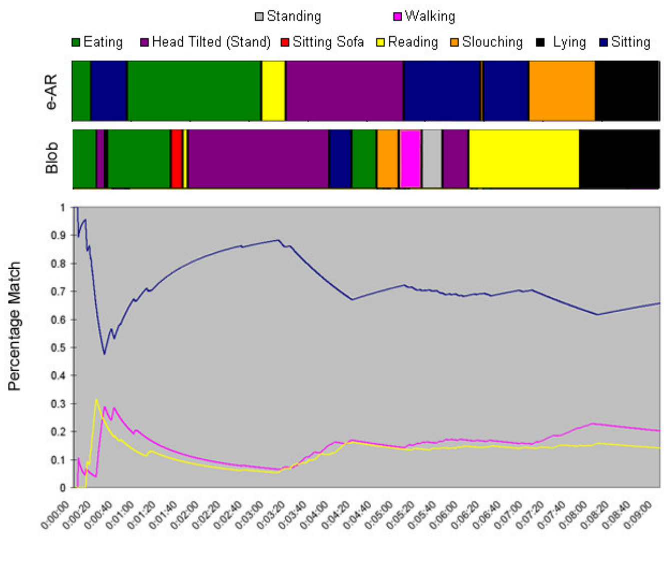

Figure 6. Traces correspond to percentage match of *e-AR* and blob sensors for same subject (blue) and simulated subjects (purple and yellow). The activities returned from the blob and *e-AR* classifiers for the real subject are also presented at the top

Location sequences from ambient sensors can be used for modelling different people's behaviour patterns. It has been demonstrated in [27] that with the use of wearable and blob based ambient sensors, it is possible to develop an practical visualization framework allowing the observation of daily activities in a homecare environment. Furthermore, an effective behaviour modelling method based on Hidden Markov Models is used for highlighting changes in activity patterns. Representation of sequences in a similarity space allows for clustering, detection of abnormalities and data-exploration. In this similarity space, it is possible to observe how close similar patterns are, and observe patients who change their behaviour, as illustrated in Figure 7.

The pattern mining technique [28] described in previous section was applied to two datasets. The datasets represent simulated activity levels for two types of users: office going and retired. Each set is compiled by using certain known activities for each type of user and a single activity can comprise a combination of one or more activity levels. Figure 8 demonstrates a visualisation of the obtained results when applying the proposed pattern mining technique to the simulated data. The structure of each day can be clearly seen and differences between users' daily routines visualised. The "Week" tree is a result of combining the five trees, which captures the general picture of the simulated routine for longer periods.

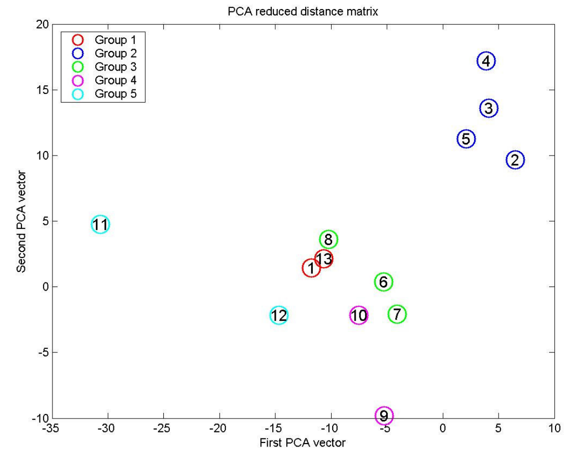

Figure 7. Each sequence of locations is represented as a circle. The graph can be used to judge similarity between un-labelled sequences and outlier can indicate deviation from normal behaviour patterns [27]

Figure 8. Routine trees showing the behaviour changes during the week for two types of users with differenct activity patterns. The bottom graph shows different activities where an activity may comprise one or more activty levels

VI. Conclusions and Future Work

The development of pervasive patient monitoring systems is an intricate job requiring the construction of appropriate sensing platforms, the integration of multiple hardware and software components and the utilisation of sophisticated data analysis algorithms. In this paper we have presented a complete framework for pervasive patient monitoring applications. Practical wearable and privacy-preserving ambient sensing paradigms were described as well as the scalable software architecture needed for sensor stream management and processing. Several potential data fusion and analysis techniques for pervasive monitoring were also presented along with some of the results obtained by applying these techniques. The framework comprises full data life cycle from acquisition to management to analysis in order to enable ubiquitous patient observation. However, it is worth noting that the framework is not fully automated, something we are planning to accomplish in the near future. Other future work areas include the development of algorithms for extracting and combining visual information that alleviate ambient visual sensing problems in case of cluttered scenes and reduce dependency of acquired data on blob sensors positions. Additional work is also required to develop improved data fusion techniques for more accurate activity detection and introduce robust autonomic behaviour profiling methods that minimise caretakers workload and enable long term elderly monitoring.

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