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SPHERE - a Sensor Platform for HEalthcare in a Residential Environment

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Abstract

Obesity, depression, stroke, falls, cardiovascular and musculoskeletal disease are some of the biggest health issues and fastest-rising categories of healthcare costs. The associated expenditure is widely regarded as unsustainable and the impact on quality of life is felt by millions of people in the UK each day. The vision of the SPHERE IRC is not to develop fundamentally-new sensors for individual health conditions but rather to impact all these healthcare needs simultaneously through data-fusion and pattern-recognition from a common platform of non-medical/environmental sensors at home. The system will be general-purpose, low-cost and scalable. Sensors will be entirely passive, requiring no action by the user and hence suitable for all patients including the most vulnerable. A central hypothesis is that deviations from a user's established pattern of behaviour in their own home have particular, unexploited, diagnostic value.

1 The SPHERE IRC

The "SPHERE" Inter-disciplinary Research Collaboration (IRC) has been developed with clinicians, social workers and clinical scientists from internationally recognised institutes including the Bristol Heart Institute, Southampton's Rehabilitation and Health Technologies Group, the NIHR Biomedical Research Unit in Diet and Nutrition and the Orthopaedic Surgery Group at Southmead hospital in Bristol. United by a shared vision, the IRC also includes a local authority that is a UK leader in the field of "Smart Cities" (Bristol City Council, BCC), a local charity with an impressive track record of community-based technology pilots (Knowle West Media Centre, KWMC) and a unique longitudinal study (the world-renowned Avon Longitudinal Study of Parents and Children (ALSPAC), a.k.a. "The Children of the Nineties"). SPHERE draws upon expertise from the UK's leading groups in Communications, Machine Vision, Cybernetics, Data Mining and Energy Harvesting, and from two corporations with world-class reputations for research and development (IBM, Toshiba).

Working hand-in-hand with the local community through BCC and its partners at KWMC, SPHERE is developing practical, user-accepted technologies and pilot systems in a large number of homes over extended periods of time. Leading clinicians in Heart Surgery, Orthopaedics, Stroke and Parkinson's Disease, and recognised authorities on Depression and Obesity are embedded within the IRC.

The proposal, led by the University of Bristol in partnership with Reading and Southampton was funded in full (∼£12M) and also attracted additional investment from the Universities and industry of ∼£3M. The total resource of ∼15M is supporting a team of mostly postdoctoral researchers (with some postgraduate students). In total, including the academic co-investigators actively managing elements of the research programme, SPHERE comprises approximately 60 people.

2 Machine Learning and Data Mining for SPHERE

Investigations are underway into a wide variety of sensor technologies, including cameras, motion sensors, ambient climatic sensors and a variety of on-body sensors. Based on their performance (in terms of reliability, discriminative ability, monetary and energy costs), some subset of these sensors will be incorporated into systems to deployed in houses.

The information from the individual sensors must be preprocessed, integrated and mined to provide a most likely model of activity which maximises information content in a health monitoring context. Moreover, the decision-making process (e.g., distinguishing between regular activities and medical emergencies) needs to be implemented and fine-tuned taking into account the specific characteristics of sensors and people.

2.1 Feature Construction and Selection

The interpretation of the preprocessed sensor data to identify meaningful features in the data requires understanding of the data generation process and hence will be closely coupled to the development of the individual sensing modalities in the initial phase of the project. The approach being taken selects features through the discovery of subgroups that behave significantly differently with respect to a particular target [1] and exploits those features in modelling customer behaviour through user profiles.

One of the main hypotheses underlying the SPHERE IRC is that many weak signals from particular sensors can be fused into a strong signal allowing meaningful health-related interventions. A necessary step here is signal calibration, for which the team will apply a range of techniques including powerful nonparametric methods derived from the ROC convex hull [2]. Further fusion arises from the combination of multiple (homogeneous or heterogeneous) sensor-level signals with knowledge of the kinematics and bio-mechanics of movement [3, 4], and with information regarding the wider context such as the time of the day etc.

Based on the calibrated and fused signals, the system must decide when to intervene and which intervention to recommend; interventions will need to be information-gathering as well as health providing. Existing approaches to this exploitation-exploration dilemma of machine learning will be extended to address the challenges of costly interventions and complex data-structures [5]. Interfaces will need to communicate (visualise) the data, such that it is informative, assists in decision-making and helps to influence improved health behaviour; this includes communicating uncertainty and conflicts within data.

2.2 Background Knowledge and Operating Contexts

Data mining and decision making needs to be contextualised and in this case will be situated within a wide body of non-trivial health-related background knowledge including knowledge of the human subjects, of their likely activities and of their medical condition(s). We will draw on previous work in incorporating and utilising structured background knowledge into the data mining process to build better models that are highly explanatory [6]. The operating context will however inevitably vary from training to deployment and between different deployment situations; an example is the use of signal detection theory to adapt the false positive rate to varying costs.

2.3 Quantification of Uncertainty

When dealing with multiple sensors in a real-world environment, we are faced with many different sources of uncertainty. At a basic level, we might have sensors that are simply not working, or that are giving incorrect readings. More generally, a given sensor will at any given time have a particular signal to noise ratio, and the types of noise that are corrupting the signal might also vary. One approach to solving this is to use standard signal processing techniques to try to clean up the signal before performing learning. However, this means that potentially useful information about the levels of uncertainty in the information has been effectively thrown away.

As a result we need to be able to handle quantities whose values are uncertain, and we need a principled framework for quantifying uncertainty which will allow us to build solutions in ways that

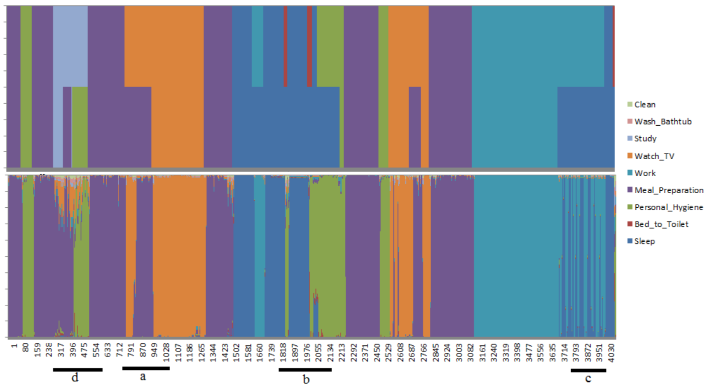

Figure 1: Demonstration of the ground truth activity labels (top) and predictions from the CRF (bottom). Co-occurring activities are seen when multiple colours are seen the upper image. Regions marked with a and c identifies co-occurring activities, b shows mislabelled activities and d marks an false negative activity.

can represent and process uncertain values. The approach we will take will be to build a model of the data-generating process, which directly incorporates the noise models for each of the sensors. Probabilistic graphical models, coupled with efficient inference algorithms, provide a very flexible foundation for such model-based machine learning [7]. The probabilistic programming language Infer.NET [8], which has been widely used in practical applications, will allow us to construct and deploy these models.

2.4 Temporal Patterns and Personalisation

Many sensors provide continuous streams of data that can be mined for temporal patterns concerning behaviour that varies from individual to individual. For example, a period of inactivity at a certain time might mean an afternoon nap for one person but a medical emergency for another. Following on from previous work in trend analysis of stream data (e.g., identifying flu epidemics from Twitter [9]) will allow the system to be adapted to personal habits and circumstances. These temporal patterns can be directly built in to our model-based framework, and additionally can be learnt on both a group-wide and individual level to learn context sensitive and specific patterns.

2.5 Initial Work: Activity Classification

The Sphere project is in the process of populating a house with sensors so that, in collaboration with our clinical partners, novel data, characteristic of important medical episodes, will be recorded for later analysis. In parallel with the collection of these data, we have already begun to investigate the efficacy of employing probabilistic approaches for activity recognition on third-party on-body and smart home sensor datasets. In particular we have investigated datasets from the CASAS research group [1] [10], and our results convey the utility of conditional random fields (CRFs) [11] for classification of activities of daily living in smart home environments [12].

Figure 1 shows an example of activity prediction on smart home sensor data, where the activities being performed can be identified by the indicated colours. In this figure the ground truth and predicted activities are shown in the upper and lower images respectively. As multiple residents inhabited the testbed at the time of recording, multiple activities can be labelled as occurring concurrently; this is illustrated in Figure 1 (upper) by regions a, b, c, and d. While multiple activities may co-occur in the dataset, only one activity from the set is, in general, responsible for the individual sensor events, and so the predictions in the lower image predict only one activity at all time points. Our approach elicits good visual correspondence between ground truth and predicted activities, and we obtained a per-instance precision of $\approx 85\%$ with false negative rates of $\approx 6\%$ (see [12] for more details).

[1] http://ailab.wsu.edu/casas/datasets/

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