Bridging eHealth and the Internet of Things: the SPHERE Project

Ni Zhu, Tom Diethe, Massimo Camplani, Lili Tao, Alison Burrows, Niall Twomey, Dritan Kaleshi, Majid Mirmehdi, Peter Flach, Ian Craddock

Abstract—There is a widely-accepted need to revise current forms of healthcare provision. Of particular interest are sensing systems in the home, which have been central to a number of studies in this area. This paper presents an overview of this rapidly growing body of work, as well the implications for machine learning, with a view to uncovering a gap between the state of the art and the broad needs of healthcare services in Ambient Assisted Living (AAL). Most approaches address specific healthcare concerns, which typically results in solutions that are not able to support full-scale sensing and data analysis for a more generic healthcare service. The paper also outlines a multiple-modality sensor platform with heterogeneous network connectivity, which is under development in the Sensor Platform for HEalthcare in Residential Environment (SPHERE) Interdisciplinary Research Collaboration (IRC).

Index Terms—Internet of Things, multiple-modality sensing, Ambient Assisted Living, Machine Learning

1 Introduction

Traditional models of healthcare are being re-examined due to well-known demographic challenges. Today's ageing population and the rise in chronic health conditions is precipitating a shift towards empowering people to manage their care and wellbeing at home. In this context, advances in AAL are providing resources to improve the lived experience of patients, as well as informing necessary interventions from relatives, carers and healthcare professionals.

The current challenge for the AAL interdisciplinary research community is how to build integrated, useful and deployable systems that can close the loop from the data sensing, through processing engines, to the end users. Such systems will rely on the sensor datasets and deliver in (quasi) real-time relevant contextual information to specific end users, from clinicians or care providers to the individual whose data is being collected and processed. The premise of the work in this area is that building profiles of Activities of Daily Living (ADL) will lead to useful datasets that can scale to very large populations, supporting early diagnosis, tracking the progress of chronic diseases, informing personalised treatment, and encouraging healthy behaviour change.

These systems are composed of several subsystems and rely on various technologies, some of which are fit for purpose and some are still under development. Additional challenges arise when these technologies have to cope with multiple end users, as happens in the domestic environment. A household often comprises several people, who may have differing healthcare needs and individual preferences. For smart home systems to be effective for the detection and management of health conditions, they must provide meaningful clinical data but also be desirable to their domestic users.

This paper provides an overview of current developments in the fields of sensing, networking and machine learning, with a view to underpinning the vision of the SPHERE project. The main aim of this interdisciplinary project is to build a generic platform that fuses complementary sensor data, in order to generate rich datasets to support the detection and management of various health conditions. Specific challenges that we are addressing within SPHERE to develop an inclusive and meaningful smart home solution are:

- capability to capture and use data from a variety of sensor technologies;
- capability to support establishment of temporal, spatial and user identity relationships in the sensor data;
- generic and easily extensible data representation (ontology) and interoperability;
- support for end-user data ownership management (raw data access and privacy);
- capability to support context-aware security; and
- passing a critical threshold of user-acceptability.

This article provides the rationale for addressing these challenges. Firstly, Section 2 reviews the sensing technologies we argue are necessary for a complete system. Section 3 reviews networking technologies and in Section 4 reviews the important aspects of pattern analysis and Machine Learning (ML) in this setting. Sections 5 and 6 are devoted to a discussion of where we are in terms of complete end-to-end systems, in addition to how the SPHERE project seeks to achieve this and create a flexible template for future systems of this type.

2 Sensing Technologies in AAL

Sensing technologies have been used in AAL for a range of applications. Among existing solutions, physiological, environmental and vision sensors are frequently used for the purpose of health monitoring in the home. These help to characterise users' everyday activities for dedicated purposes by providing long-term sensing data that, in combination with ambient intelligence algorithms, contribute to behaviour pattern recognition [1]. The following subsections reflect the distinction that is frequently adopted in the literature, owing to the different data outputs and approaches required for each. However, one of the aims of SPHERE is to integrate these various sensing modalities into an Internet of Things (IoT) solution for AAL.

2.1 Physiological Signal Monitoring

Physiological signals provide original health evidence from the human body, using diverse biosensors that measure various physiological parameters [2]. These biosensors are deployed in an implantable (in-body), wearable (on-body), portable (off-body) or environmental modality. Of these, implantable sensors are the most intrusive and are listed here merely for completeness. The aspiration in AAL has been to foster comfort through unobtrusive technology.

In recent years, the advent of personal wearable devices for self-monitoring has seen research outputs and fashionable electronic gadgets moving into the consumer space. Figure 1 summarises a number of representative systems, their individual features and architectures [3][4][5]. Further research on telecare, telehealth, and telemedicine systems has improved biomedical sensing efficacy. Different concept-to-prototype systems have been proposed and implemented in response to individual healthcare issues. A typical biomedical sensing system is composed of a data acquisition module (DAQ) that collects various biomedical signals; a signal processing module; a communication gateway (normally a computer or smartphone) forwarding data over the Internet; as well as a monitoring centre. Mobile healthcare (m-Health) was introduced for telemedicine and uses smartphones and handheld devices for biomedical signal monitoring [6].

Almost all of these personal physiological signal monitoring systems can automatically synchronise data from the device with various embedded sensors to the network gateway or monitoring centre. Whilst it is promising that these wearable self-monitoring gadgets perform activity tracking to collect data on ADL, the case-analysis in Figure 1 shows that there are several issues that must be addressed for them to truly support AAL systems:

- lack of long-term, continuous, easy-to-access raw data that contains rich details of clinically-relevant information;
- lack of interoperability with other healthcare systems; and

	System	Raw data freely accessible	Multiple signals	Data aggregation	Application	Expandability
Commercial Products	Fitbit	x	✓	✓	Fitness	Limited
	Jawbone Up	x	✓	✓	Fitness	Limited
	Nike+ Fuelband SE	x	✓	✓	Fitness	x
	Pebble Steel	x	x	x	Fitness	x
	Withings blood pressure montor	✓	✓	x	Measurement of blood pressure	Limited
	Fit Shirt	✓	✓	x	Vital signs monitoring	x
	V-Patch	✓	x	x	Vital signs monitoring	x
Research Outputs	Verity AAL [3]	✓	✓	✓	Physiological signals monitoring	x
	H@H [4]	✓	✓	x	Vital signs monitoring	Limited
	Activity Recognition System [5]	✓	x	x	Activity recognition	x

Fig. 1: A list of representative physiological signal monitoring systems.

- limited expandability to adapt to new sensing data.

The technology is moving towards more comfortable and desirable wearable devices and should also build on the real-life attitudes and experiences of users. Two big challenges are the absence of ambient information related to the physiological data, and energy consumption (battery life). The former may introduce sensing cognition difficulty or even bias, and the latter is actually a bottleneck towards wearable device prosperity.

2.2 Home Environment Monitoring

A Smart Home (SH) is a system of pervasive information and communication technologies by which both the home environment and the resident interaction with the environment are monitored in an unobtrusive manner [2]. A list of sensors is given in [2], which is by no means comprehensive and has the potential to grow as the field of sensor technologies matures. Most AAL research projects will use a diverse sensor portfolio rather than single sensors in various applications, as discussed below.

Fusion of ambient-monitoring and activity detection techniques is capable of sensing an environment and recognising various activities or events. Figure 2 provides an overview of some existing sensors and technology types, as well as their application in a healthcare setting [7]. It is not an exhaustive summary but a representative list for demonstration of different sensor modality usage. One prominent area of application is fall detection reviewed in [8], using wearable, ambient and camera based approaches. Accurate localisation within the home environment is an important component in AAL applications [9]. Many ambient sensor systems were applied to address different health issues, such as mental health, emotional state, sleep measures, Diabetes and Alzheimer's Disease [10]. Those sensing technologies have been used to monitor individual daily activities, aiming to gain health assessment and detect deviation from the user's behaviour pattern. A good example is the CASAS [11] project that treats environments in SH as intelligent agents, based on technologies of ML and pervasive computing.

Different versions of SH systems were designed for different purposes including managing energy consumption, healthcare, home automation and home entertainment. All these provide rich datasets of ADL but, even though the data are available and can be used in helping to identify behaviour profiles that reflect users' daily activities, they have been relatively underexplored and integrated as indicators of health and wellbeing. The major challenge in this space is system and data integration for different commercially available devices to support user-friendly configuration [12]. The datasets generated from those different SH systems are disaggregated or less-efficiently manipulated by advanced ML algorithms. A truly generic AAL system of systems that creates knowledge-based context-aware services for AAL is yet to be realised [13].

2.3 Vision-based monitoring

Intelligent visual monitoring has received a great deal of attention in the past decade, for example due to increased interest in smart healthcare systems in the home environments [14]. Although a wide variety of sensing technologies can be used in in-home assistive systems, visual sensors have the potential to address several limitations of current systems: they do not require the user to wear them and they are able to simultaneously detect multiple events.

Analysis of human motion by way of visual information has been achieved through the use of multi-camera architectures in indoor and outdoor environments [15], by using *centralised* or *distributed* platforms predicated on processing requirements and scalability issues. Recently, human motion analysis algorithms have dramatically improved through the combination of colour cameras and depth sensors. The main advantages of depth sensors are their low cost and their ability to provide real-time dense depth data without intensive processing. These devices allow the extraction of detailed 3D information of a scene, which boost the ability to detect the human shape. However, they suffer from several limitations: interference from natural light, scattering, and limited range. Although visual data provides rich information, most of them may involve individuals' privacy. Therefore, different methods for ensuring privacy protection in videos and images are proposed as shown in [14].

Intelligent video analysis can lend itself well to many application areas in health monitoring. Systems for daily life assistance have been designed for monitoring people with dementia, measuring sleeping-respiration, and tracking medication habits [16]. Vision systems can also feature in infotainment gadgets that have fuelled research interest in their use in healthcare applications [17]. However, works based solely on computer vision techniques for monitoring and clinical evaluation of movement disorders are still in their infancy.

Fall detection is a major challenge in healthcare for the elderly, and video-based technologies have many advantages over popular wearable alarms, since they do not require action from the user and are always active. Recently RGB-Depth (RGB-D) devices have been used successfully for this task, which outperform other sensing technologies [8]. The use of staircases can directly reflect musculoskeletal problems and the progress of recovery, and more recently, a general method for online estimation of the quality of movement on stairs was proposed in [18].

Main limitations of video-based systems are due to cluttered environments, occluded scenes and unstable lighting conditions. Even if these issues can be reduced by employing multiple cameras or complementary devices, such as depth sensors, they are still open problems to be tackled by integrating the information provided by different environmental sensors. Moreover, in most real world applications, analysing and processing data in real time is paramount, but most existing methods have difficulty achieving this due to their computational demands. The lack of a comprehensive and realistic dataset is also an issue.

3 Networking Technologies for Smart Homes

Existing networking technologies play an increasingly prominent role in modern AAL designs. In-home communications are well supported and their performance, from a communication system perspective, is relatively well understood. The technologies listed here for completeness are stable and mature. Current research is focusing on incorporating different communication technologies into clinical applications, which is also driven by the use of heterogeneous devices with diverse communication protocols. What enables sensing platforms with the functionality of remote monitoring is ubiquitous network connectivity to close the loop between residents and clinicians.

Application	Sensing Modality	Suitable Sensor Type
Falls	Environment	Floor sensor, Infrared (IR) sensor, microphone, pressure sensor
	Wearable	Accelerometer
	Video	RGB camera, depth sensor
Indoor localisation	Environment	Ultra Wideband (UWB), Wireless LAN, (WLAN), IR, ultrasound, physical contact, differential air pressure
	Wearable	RFID, Bluetooth-enabled device
	Video	RGB camera, depth sensor
ADL recognition	Environment	Passive IR (PIR), light, microphone, television IR sensor, weather conditions, including internal and external light levels, and temperatures, pressure, humidity, smart meters
	Wearable	accelerometer, blood pressure sensor, blood glucose monitors
	Video	RGB camera, depth sensor, time-of-flight camera, thermal infrared imagery
Anomaly detection	Environment	PIR, microphone, IR sensor, weather conditions including internal and external light levels and temperatures, pressure, humidity, solar average rate, wind speed and direction
	Wearable	tri-axial accelerometer, blood pressure sensors and blood glucose sensors
	Video	RGB camera, depth sensor, infrared imagery

Fig. 2: Sensor taxonomy of environment, wearable and video sensing modalities used in ambient monitoring and activity detection.

Due to existing in-home infrastructures, wired technologies commonly provide high data transmission rates. Among these, Power Line Communication (PLC) technologies are evolving in the field of smart home applications, especially Advanced Metering Infrastructure (AMI) and Automated Home Energy Management (AHEM). Widely adopted systems use X10, KNX and ITU-T G.Hn, IEEE 1901 [2].

Various wireless networking technologies and communication protocols were summarised in [19]. Figure 3 lists some of the typical short-range wireless technologies used. WiFi™, apart from those non-IP enabled technologies, has the significant advantage of being Internet Protocol (IP) enabled. However, hardware with WiFi™ connectivity is still relatively power hungry, and it is less suitable for battery-powered sensor motes in applications anticipating long-term deployment. To break down this barrier, an adaptive sub-layer 6LoWPAN was introduced to enable IPv6 onto low-power processing-limited embedded hardware over low-bandwidth wireless network. An energy-efficient Wireless Sensor Network (WSN) solution will improve AAL system user experience and requires less maintenance effort.

There are several basic factors for adopting these networking technologies, such as guaranteeing the necessary communications throughput, the power consumption and the cost of hardware. Beyond those elements, to fully underpin a multi-modality sensor system in the SH, the major function of IoT infrastructure is to provide ubiquitous connectivity and interaction to all the sensing devices in a heterogeneous network circumstance. Additional advantages over allowing access to existing Internet infrastructures can be gained by IP-enabled sensing networks, removing the need for translation gateways or proxies in hardware and software, and thus creating more seamless integrated AAL systems. Data collecting points in WSN must have identifiers to be manipulated. If a unique 'name' to the sensor is defined by an IP (more likely IPv6) address, the data collecting point can be addressable in the Internet through the whole end-to-end system.

Other important standards such as UPnP/DLNA, ECHONET, OSGi and Continua Health Alliance were reviewed in [20], which also indicated that a significant barrier to their widespread use is limited compatibility; overlay networking protocols and metadata

Technology	Frequency Band	Bit Rate	Network Topology	Maximum Nodes	IP Enabled
IEEE 802.15.4	868/915 MHz/2.4 GHz	20/40/250 kbps	P2P, Star	Implementation dependent	No
ZigBee	868/915 MHz/2.4 GHz	20/40/250 kbps	P2P, Star, Mesh (Tree)	>64000	No
BLE	2.4 GHz	1 Mbps	P2P, Star	Implementation dependent	No
WiFi™	2.4/5 GHz	<600 Mbps (11n)	Star	Implementation dependent	Yes

Fig. 3: Short-range wireless networking technologies in the home.

technologies were introduced to attempt to solve this problem.

All AAL systems are built around a gateway device. This provides facilities for remote access to the sensor data, and to connect and bridge diverse networks. The home gateway implements multiple functions, such as local monitoring/controlling centre, intelligent agents, network management. Saito [21] reviewed the home gateway from a broad, practical perspective, and proposed a home gateway architecture suitable for better implementation and management. Middleware solutions embedded in the gateway, in the context of sensing platform for healthcare and wellbeing in the SH, address the fusion of different clusters of sensors, coordinating and managing these highly heterogeneous systems. Several works address AAL systems specifically, since often middleware solutions are designed for different application domains. For example, openAAL middleware defines a framework on top of the Open Service Gateway initiative (OSGi) specification to facilitate integration and communication between services, including Context Manager, Procedural Manager and Composer [22]. A key factor for the IoT infrastructure successfully enabling AAL systems is to provide loosely coupled functionality, allowing auto-configuration and dynamic interoperability amongst not only all devices but end users.

4 Pattern Analysis and Machine Learning

The performance of different sensor technologies, in terms of reliability, discriminative ability, monetary and energy costs, is context-dependent. Readings from individual sensors must be preprocessed, integrated and mined to provide a most likely model of activity which maximises information content in the given health monitoring context. Moreover, the decision-making process must be implemented and fine-tuned, and in particular it must consider the contextual knowledge of sensors and individuals.

Whilst there have been some advances in applying ML techniques to ADL, an end-to-end system does not currently exist. What follows is a discussion of the state of the art of individual elements of such a ML system.

4.1 Quantification of Uncertainty

Multiple heterogeneous sensors in a real world environment introduce 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.

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 can represent and process uncertain values. A compelling approach is to build a model of the data-generating process, which directly incorporates the noise models for each of the sensors. Probabilistic (Bayesian) graphical models, coupled with efficient inference algorithms, provide a principled and flexible modelling framework [23].

4.2 Feature Construction, Selection, and Fusion

Given an understanding of data generation processes, the sensor data can be interpreted for the identification of meaningful features. Hence it is important that this is closely coupled to the development of the individual sensing modalities [24], e.g. it may be that sensors have strong spatial or temporal correlations or that specific combinations of sensors are particularly meaningful.

One of the main hypotheses underlying the SPHERE project [25] is that once calibrated, many weak signals from particular sensors can be fused into a strong signal allowing meaningful health-related interventions [26].

Based on the calibrated and fused signals, the system must decide whether intervention is required and which intervention to recommend; interventions will need to be information gathering as well as health providing. This is known as the exploration-exploitation dilemma, which must be extended to address the challenges of costly interventions and complex data-structures [27].

4.3 Adapting to Context and Domain Knowledge

Data mining and decision making need to be contextualised and situated within a wide body of non-trivial health-related background knowledge, which in turn requires highly explanatory models [28]. The operating context will vary from training to deployment, between different applications, residents and households, and so incorporation of methods that are robust to these variations are critical.

Continuous streams of data can be mined for temporal patterns that vary between individuals. These temporal patterns can be directly built into the model-based framework, and additionally can be learnt on both group-wide and individual levels to learn context sensitive and specific patterns. For a recent review of methods for dealing with multiple heterogeneous streams of data in an on-line setting see [29].

Finally, interfaces will need to communicate the data and predictions. Such communications must be informative and assist in decision-making to influence improved health behaviour. This includes communicating uncertainty and conflicts within data, which is increasingly being seen as an important issue [30].

5 The Way Forward

The overview presented in the previous sections, even at a high level, reveals certain gaps and challenges arising due to the multi-disciplinary nature of the systems required to provide AAL data and applications for healthcare purposes in home environments. Some of these challenges are not unique to eHealth, but are arising in more application fields where researchers and industry are looking to use data collected in multiple domains and using multiple technological systems, not necessarily designed or even deployed together, in order to bring together a cohesive, stable, and reliable view of the measured activities.

The initial hypothesis for SPHERE, as well as other similar AAL platforms, is that understanding ADL may give insights into health-impacting behaviour, or even evidence of the existence of health conditions. The hypothesis is based on the expectation that unique stable patterns can be detected in ADL, and these will be significant and useful at both population and individual levels. Testing this hypothesis satisfactorily requires multi-modal, interoperable and replicable IoT systems for AAL that produce comprehensive, context-rich, verifiable and longitudinal data sets with statistically significant user populations. We have argued in this paper that no single sensing technology domain is capable of providing such datasets that can be used with confidence to identify insightful context for AAL, owing at least in part to the user acceptance of certain technologies. Whilst existing achievements are inspiring, an AAL system based on an insufficient number of sensing technologies cannot fully represent the context, complexity and variety of daily living. Furthermore, we have shown that, for reasons of cost, time, and user acceptance, the acquired data reported by historical and existing studies is only partially able to exploit anticipated synergies for health and wellbeing applications. SPHERE is addressing this by building a multi-modality sensing system as an infrastructure platform fully integrated, at design stage, with intelligent data processing algorithms driving the data collection.

In this paper, single-domain technologies and networking have been shown to be mature enough to properly enable eHealth architectured systems. Whilst individual technologies will continue to be developed, whether wireless or wired, the main challenge remains the design of an analytics-driven data-gathering platforms that provide a rich-set of data efficiently, reliably and on-demand. This then can be used to test the hypothesis that ADL data is useful for a range of health and wellbeing purposes, as it is widely envisaged.

The premise for the SPHERE project is the fact that we do not know what data is necessary to drive analytics for ADL identification and standardisation across different homes, and that single-modality sensing platforms cannot answer this question fully. Therefore SPHERE has developed a multi-modality sensing platform for collecting data from 100 houses in the Bristol area. The overall architecture, which follows a clustered-sensor approach, is shown in Figure 4 and is currently installed and running in a real house in Bristol (the SPHERE House).

The SPHERE system uses three sensing technologies: environment, video, and wearable sensing. The environment sensors include humidity, temperature, air quality, noise level, luminosity, occupancy, door contacts, and utilities (water, gas, electricity) consumption, centrally and at appliance/faucet level. The currently deployed system uses 40 nodes providing more than 90 data points, all structured and timestamped to establish context and temporal relationships. The video sensors are RGB-D devices which are placed in various locations, such as the living room, kitchen, corridor/hall and staircases. The video sensors allow us to obtain residents' cadence, gait and 3D trajectory throughout the smart environment. The wearable sensors are Bluetooth Low Energy (BLE) devices with dual accelerometer data, and support dual operation mode (connection-oriented and extra-low energy connectionless communication modes) to be able to provide full 50Hz accelerator measurements in addition to localisation service. The data from each sensor cluster is collected in a SPHERE Home Gateway, which maintains time synchronisation in the system and, in addition, controls data access to ensure user privacy. The data from the SPHERE Home Gateway is collected by a heterogeneous data management platform (SPHERE Data Hub), which manages data access and will allow a dynamic library of data analytics services to be available for registered end users. The current system is operational and is undergoing scripted validation experiments, where multiple sensor domain data are processed to establish ADL against external (manual or automatic) activity tagging. Upon deployment, the data from the environment, wearable and camera sensing sub-systems are tasked to be fused and processed in real-time for activity and health monitoring in longitudinal and focused studies. One of the key objectives of the SPHERE project is to deliver datasets with a strong focus on the richness of meta-data annotations, as well as the experimental and user contexts in order to provide to the wider research community a platform for improved understanding of their roles in behavioural trends for healthcare.

6 Conclusions

There is a widely-accepted need to revise current forms of healthcare provision, in particular in a residential context. One of the most promising approaches lies in the hypothesis that by trying to understand how we live our lives in the home and establishing if routine activities exist, then changes in these activities can act as indicators of underlying health-related issues or behaviour in the general population. To satisfactorily verify this hypothesis requires linking together seamlessly in an AAL platform the two pillars of data-collecting infrastructure and analytics. The discussion in the review sections of this paper shows that whilst the networking and communication technology challenges will continue to be addressed in their respective domains, the biggest gap is to establish a clear link between the data-gathering infrastructure and data analytics by designing the infrastructure with the data analytics in mind (i.e. defining what data is needed to be collected rather than doing the best one can with the data available). It is clear that single-modality sensing systems provide insufficient data sets to allow verification of the hypothesis of the link between ADL changes and health-related conditions or behaviour for general population. Whilst designing AAL platforms that integrate multi-modality sensing systems is not cheap, it is the only way to address this hypothesis conclusively. To this end the SPHERE IRC has designed a multi-modal AAL IoT system driven by data analytics requirements. The system is under test in a single house, and will be deployed in a general population of 100 homes in Bristol (UK), and the data set collected will be made available to the AAL research community.

Acknowledgement

The SPHERE IRC includes 40+ researchers working together and contributing to the SPHERE vision. The authors acknowledge fully the valued contribution, discussions and exchange of ideas that have influenced the analysis in this paper. A full list of SPHERE collaborators can be found at http://www.irc-sphere.ac.uk.

This work was performed under the SPHERE IRC funded by the UK Engineering and Physical Sciences Research Council (EPSRC), Grant EP/K031910/1.

References

[1] L. Chen, C. D. Nugent, J. Biswas, and J. Hoey, *Activity Recognition in Pervasive Intelligent Environments*. Atlantis Publishing Corporation, 1st ed., 2011.

[2] M. R. Alam, M. B. I. Reaz, and M. A. M. Ali, "A review of smart homes: Past, present, and future," *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, vol. 42, no. 6, pp. 1190–1203, 2012.

[3] J. Winkley, P. Jiang, and W. Jiang, "Verity: an ambient assisted living platform," *Consumer Electronics, IEEE Transactions on*, vol. 58, no. 2, pp. 364–373, 2012.

[4] L. Fanucci, S. Saponara, T. Bacchillone, M. Donati, P. Barba, I. Sanchez-Tato, and C. Carmona, "Sensing devices and sensor signal processing for remote monitoring of vital signs in chf patients," *Instrumentation and Measurement, IEEE Transactions on*, vol. 62, pp. 553–569, March 2013.

[5] P. Gupta and T. Dallas, "Feature selection and activity recognition system using a single triaxial accelerometer," *Biomedical Engineering, IEEE Transactions on*, vol. 61, pp. 1780–1786, June 2014.

[6] S. Adibi, "Link technologies and Blackberry mobile health (mHealth) solutions: A review," *Information Technology in Biomedicine, IEEE Transactions on*, vol. 16, no. 4, pp. 586–597, 2012.

[7] G. Deak, K. Curran, and J. Condell, "A survey of active and passive indoor localisation systems," *Computer Communications*, 2012.

[8] M. Mubashir, L. Shao, and L. Seed, "A survey on fall detection: Principles and approaches," *Neurocomputing*, vol. 100, pp. 144–152, 2013.

[9] P. Barsocchi, S. Chessa, F. Furfari, and F. Potorti, "Evaluating ambient assisted living solutions: The localization competition," *Pervasive Computing, IEEE*, vol. 12, no. 4, pp. 72–79, 2013.

[10] G. Acampora, D. Cook, P. Rashidi, and A. Vasilakos, "A survey on ambient intelligence in healthcare," *Proceedings of the IEEE*, vol. 101, pp. 2470–2494, Dec 2013.

[11] D. J. Cook, M. Schmitter-Edgecombe, *et al.*, "Assessing the quality of activities in a smart environment," *Methods Inf Med*, vol. 48, no. 5, pp. 480–485, 2009.

[12] S. Mennicken, J. Vermeulen, and E. M. Huang, "From today's augmented houses to tomorrow's smart homes: New directions for home automation research," in *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, UbiComp '14, (New York, NY, USA), pp. 105–115, ACM, 2014.

[13] P. Rashidi and A. Mihailidis, "A survey on ambient-assisted living tools for older adults," *Biomedical and Health Informatics, IEEE Journal of*, vol. 17, no. 3, pp. 579–590, 2013.

[14] A. A. Chaaraoui, J. R. Padilla-López, F. J. Ferrández-Pastor, M. Nieto-Hidalgo, and F. Flórez-Revuelta, "A vision-based system for intelligent monitoring: Human behaviour analysis and privacy by context," *Sensors*, vol. 14, no. 5, pp. 8895–8925, 2014.

[15] S. Soro and W. Heinzelman, "A survey of visual sensor networks," *Advances in Multimedia*, vol. 2009, 2009.

[16] S.-R. Ke, H. L. U. Thuc, Y.-J. Lee, J.-N. Hwang, J.-H. Yoo, and K.-H. Choi, "A review on video-based human activity recognition," *Computers*, vol. 2, no. 2, pp. 88–131, 2013.

[17] Q. Ding, I. Stevenson, N. Wang, W. Li, Y. Sun, Q. Wang, K. Kording, and K. Wei, "Motion games improve balance control in stroke survivors: a preliminary study based on the principle of constraint-induced movement therapy," *Displays*, 2012.

[18] A. Paiement, L. Tao, S. Hannuna, M. Camplani, D. Damen, and M. Mirmehdi, "Online quality assessment of human movement from skeleton data," in *British Machine Vision Conference (BMVC)*, 2014.

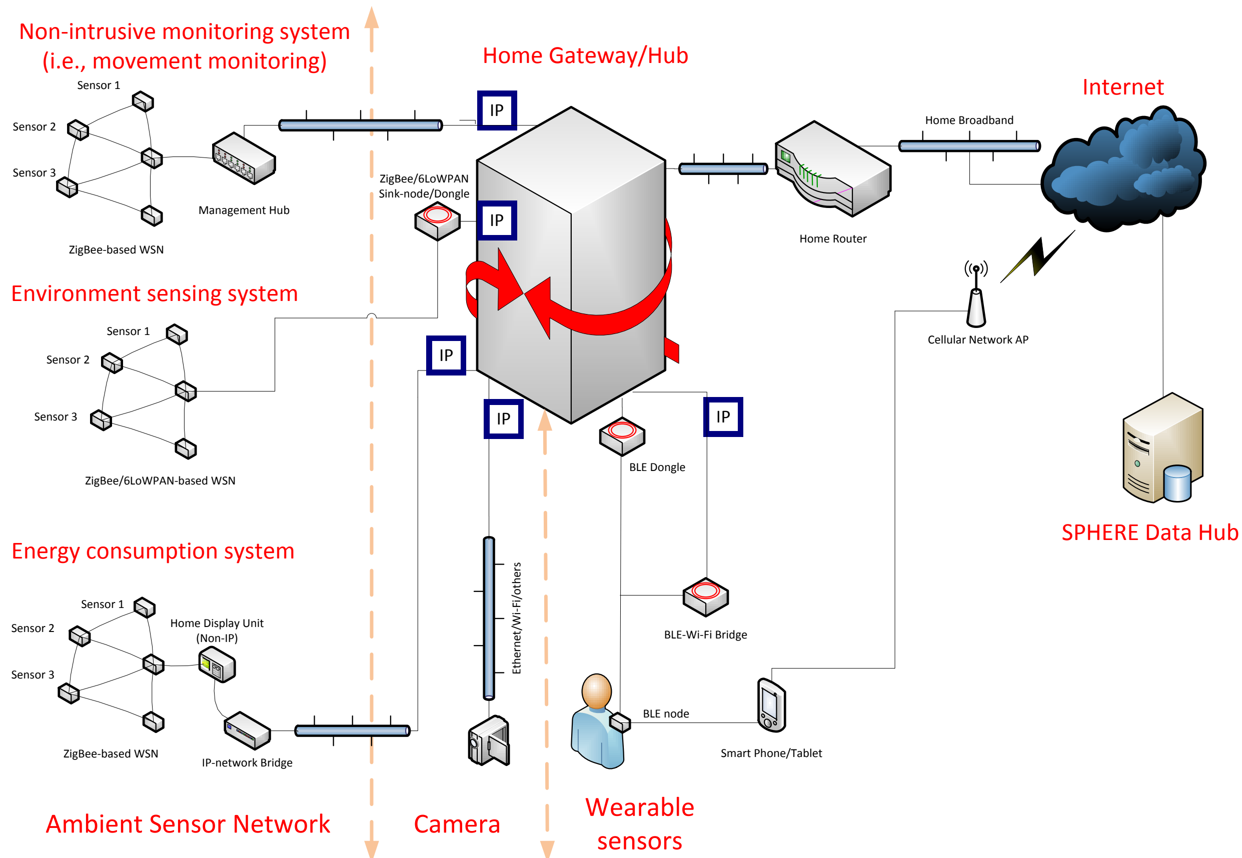

Fig. 4: The proposed system scenario of the sensing platform.

[19] H. Alemdar and C. Ersoy, "Wireless sensor networks for healthcare: A survey," *Computer Networks*, vol. 54, no. 15, pp. 2688–2710, 2010.

[20] N. Ishikawa, "PUCC activities on overlay networking protocols and metadata for controlling and managing home networks and appliances," *Proceedings of the IEEE*, vol. 101, pp. 2355–2366, Nov 2013.

[21] N. Saito, "Ecological home network: An overview," *Proceedings of the IEEE*, vol. 101, pp. 2428–2435, Nov 2013.

[22] P. Wolf, A. Schmidt, J. Otte, M. Klein, S. Rollwage, B. König-Ries, T. Dettborn, and A. Gabdulkhakova, "openAAL - the open source middleware for ambient-assisted living (AAL)," in *AALIANCE Conference, Malaga, Spain*, 2010.

[23] C. Bishop, "Model-based machine learning," *Phil Trans R Soc A*, vol. 371, 2013.

[24] H. Liu and H. Motoda, *Feature extraction, construction and selection: A data mining perspective*. Springer, 1998.

[25] T. R. Diethe, N. Twomey, and P. Flach, "Sphere-a sensor platform for healthcare in a residential environment," *Large-scale Online Learning and Decision Making Workshop*, 2014.

[26] L. A. Klein, *Sensor and data fusion: a tool for information assessment and decision making*, vol. 324. Spie Press Bellingham, WA, 2004.

[27] B. C. May, N. Korda, A. Lee, and D. S. Leslie, "Optimistic bayesian sampling in contextual-bandit problems," *J. Mach. Learn. Res.*, vol. 13, pp. 2069–2106, June 2012.

[28] T. Gärtner, J. W. Lloyd, and P. A. Flach, "Kernels and distances for structured data," *Machine Learning*, 2004.

[29] T. Diethe and M. Girolami, "Online learning with (multiple) kernels: a review," *Neural computation*, vol. 25, no. 3, pp. 567–625, 2013.

[30] L. Rosenbaum, "Communicating uncertainty — Ebola, public health, and the scientific process," *New England Journal of Medicine*, vol. 372, no. 1, pp. 7–9, 2015.