Adaptive Smart Environments: Detecting Human Behaviour from Multimodal Observation

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***Abstract*—It is desirable to enhance the social capabilities of a smart home environment to become more aware of the context of the human occupants' activities. By taking human behavioural and contextual information into account, this will potentially improve decision making by the various smart house systems. Full mesh Wireless Sensor Networks (WSN) can be used for passive localisation and tracking of people or objects within a smart home. By monitoring changes in the propagation field of the monitored area from the link quality measurements collected from all the nodes of the network, it is feasible to infer target locations. It is planned to apply techniques from Radio Tomographic Imaging (RTI) and machine vision methods, adapted to the idiosyncrasies of RTI, which will facilitate real-time multiple target tracking in the University of Hertfordshire Robot House (UHRH). Using the Robot Operating System (ROS) framework, these data may then be fused with concurrent data acquired from other sensor systems (e.g.) 3-D video tracking and ambient audio detection in order to develop a high level contextual data model for human behaviour in a smart environment. We present experimental results which could provide support for human activity recognition in smart environments.**

Keywords–radio tomography; device-free passive localisation; wireless sensor networks; human-computer interaction; sensor fusion.

I. Introduction

There is a clear and obvious need for reliable person location sensing systems in smart environments and assisted living environments that make life more convenient and more secure for people. The convenience of automated control of lighting, heating and other electrical consumer devices is increasingly being teamed with domestic or service robots as elements within a smart home. Robots are increasingly seen as one of the main ways by which the smart home systems can interact face to face with the human occupants, as well as directly perform assistive tasks. A consequence of convergent multiple underlying technologies is the emergence of the paradigm of ubiquitous computing, also described as pervasive computing or ambient intelligence or the "Internet of Things" [1], [2]. There are also significant benefits to the wider global community derived from more efficient use of resources. In parallel with increasing global pressure on dwindling energy reserves, we are also witnessing the pressures that an ageing population places on already over-stretched health and social welfare services. Converting ordinary homes to smart living environments will require the development of unobtrusive, passive, device-free person tracking and localisation systems which are simple to install, operate and maintain. Gathering human activity information from a variety of sensor data coupled with machine learning algorithms is critical to the development of a wide variety of applications used to monitor and track the functional status of residents. The eventual aim of this current research is to enhance the social capabilities of a smart environment so enabling it to become more aware of the context of current human activities and to take this contextual information into account in order to improve the smart home systems' Artificial Intelligence (AI) assistive decision making.

The potential use of wireless sensor networks (WSN) for passive human localisation and tracking systems affords numerous desirable characteristics. In particular, people are not required to carry or wear any electronic transceiver equipment of any kind. Consequently the system performance is not affected by such human attributes as forgetting to carry or wear devices and is also able to accommodate the presence of visitors (or intruders). The convergence of advances in the key technology areas of digital microelectronics, micro-electro-mechanical systems (MEMS) and wireless communications have led to an expanding ecosystem of low cost, low-power sensor node devices which are capable of forming self-organising cooperative ad-hoc short-range radio frequency (RF) WSN [3]. WSN technology deployed within a smart environment allows unobtrusive person-tracking without the need for the person(s) being tracked to carry a transmitting device. This is also known as Device-free Passive Localisation (DfPL).

Objects moving through the space where the WSN operates result in a perturbation of the radio links. Received Signal Strength (RSS) is one of the metrics built into 802.15.4-compliant wireless nodes, another being Link Quality Indicator (LQI), both of which are discussed in the technical note at Section 2 below. Radio Tomographic Imaging (RTI) exploits these RSS fluctuations caused by multipath propagation of the radio signals as they deviate from their line of sight path due to shadowing, reflection, diffraction or scattering [4].

RTI technology is integral to the proposed sensor-based research described here. A methodology summary can be derived from the first key paper describing the work of Bocca et al. [5] in the development of RTI as a reliable DfPL technology application for multiple target tracking (see data processing steps in outline at Section 5 below). The

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objective is to estimate the change in the propagation field of the monitored area from the RSS/(LQI) measurements collected from all the links on the network.

Sensor fusion is also integral to this current research and a methodology summary derived from the second key paper describing the work of Brdiczka et al. [6] in the development of multimodal smart environment observation is presented at Section 3 below.

The remainder of this paper is organised as follows: Section 2 discusses related work. Section 3 discusses research challenges and goals. Section 4 describes how the WSN has been created and an analysis and discussion of initial studies are depicted. In Section 5 planned studies are outlined. Finally we identify future research and conclude this paper in Section 6.

II. RELATED WORK

The eventual aim of the work presented here is the recognition of everyday human activity, more formally referred to as Activities of Daily Living (ADL), for example, through the use of multiple sensors installed in a smart home environment. ADL include routines such as dressing/bathing, eating, ambulating (walking), toileting and hygiene [7]. Associated with each activity there will typically be at least one basic action such as opening or closing a drawer or cupboard, fetching a utensil etc.

Cook and Das [8] define a smart environment as "a small world where different kinds of smart device are continuously working to make inhabitants' lives more comfortable". Smart environments are envisioned as the by-product of inexpensive and pervasive computing, thus making Human-Computer Interaction (HCI) with the system a pleasant and intuitive experience.

A typical DfPL system currently employs a variety of sensing devices including video camera systems and physical contact sensors [9] for people and object localisation and tracking. Other DfPL systems make use of light sources and sensors [10]. Fink and Beikrich [11] usefully classify DfPL systems employing radio signals into three main categories based on measurement principles:

i. Radar-based systems which utilise trigonometry (range and angle) derived from reflected and scattered return signals [12], [13];

ii. RF-based systems which analyse attenuation of received signal strength (RSS) values on wireless links between nodes. This technique, known as RTI, while capable of monitoring large spatial volumes such as warehouses, homes and offices, is limited to line of sight (LOS) setups [4];

iii. Variance-based RTI (VRTI) systems which analyse RSS fluctuations in multipath fading environments and permit non line of sight (NLOS) localisation [14].

In a smart environment, information about human behaviour and activities can be acquired from different types of detectors, each with its own data acquisition framework or 'modality'. Brdiczka et al. [6] describe their approach to addressing learning and recognition of human behaviour models from multi-modal observations in one such smart home environment. Multi-modal observation is an innate human concept where use of combined senses is essential to the detection and discrimination of incoming signals from the environment. Consequently some multi-modal applications are based on imitating aspects of natural multi-modal sensing, with audio-visual being the most prevalent. Sensor data fusion is the combining of sensor data derived from disparate sources, such that the resulting information has less uncertainty than would be possible when these sources were used individually. Feature extraction is a key component of 3-D video tracking, but is computationally expensive as well as being context insensitive. A potential alternative to 3-D video tracking is the use of RTI in order to acquire changes in RSS and WSN link quality information (LQI) caused by moving people and objects in the monitored area [4]. RTI is a promising WSN-based imaging technique developed by Bocca, Patwari, Wilson et al. [4], [5] which is computationally less expensive than 3-D video processing and can operate in real- time. Compared to other sensing technologies applied in motion tracking, such as infrared, ultrasonic range finders [15], ultra-wideband (UWB) radios [16] and video cameras [17], WSN provides several advantages: they work in the dark and can penetrate smoke and walls; they are less invasive in domestic environments than video camera networks [18], they are significantly less expensive than UWB transceivers and their installation and maintenance time is minimal. The current work explores the possibility of using RTI for sensor fusion and machine learning as a component in a multi-modal smart environment. Bocca et al. [5] describe a state of the art RTI system which operates in real time. Our intention is to replicate or adapt aspects of their methodology, alongside the methodology of Brdiczka et al. [6] and to incorporate it into the experimental work. These data may then be fused with, or evaluated against contemporaneous data acquired from other sensor systems (e.g.) 3-D video tracking, speech and ambient audio detection, reed switches, pressure mats, etc. in order to develop a high level contextual data model for human behaviour in a smart home environment.

A. Technical note concerning RSS & LQI

1) Received Signal strength (RSS): RSS decreases with distance according to the following equation:

$$\mathrm{RSS} = -(10\mathbf{n}\log_{10}\mathbf{d} + \mathbf{A}) \tag{1}$$

Where,
n = signal propagation constant (propagation exponent)
d = distance from sender
A = received signal strength at a distance of 1 meter

RSS is a measure of how the configured transmission Power at the Transmitting device (PTx) directly affects the received signal Power at the Receiving device (PRx). In embedded RF devices, the RSS is converted to a Received Signal Strength Indicator (RSSI) which is defined as the ratio of the received Power to the ReFerence power (PRF). Typically the reference power represents an absolute value of PRF = 1mW, RSSI is typically expressed in dBm:

$$\mathrm{RSSI} = 10 * \log(\mathrm{PRX}/\mathrm{PRF}) \tag{2}$$

2) Link quality indicator (LQI): IEEE 802.15.4 radio devices provide applications with information about the incoming signal. The effect of distance and interference on RSS can be measured by the packet success rate, RSSI and LQI provided by the radio. LQI is a metric introduced in IEEE 802.15.4 that measures the error in the incoming modulation of successfully received packets (packets that pass the Cyclic Redundancy Check (CRC) criterion).

LQI measures each successfully received packet and the resulting integer ranges from 0x00 to 0xFF (0-255), indicating the lowest and highest quality signals detectable by the receiver (between -100dBm and 0dBm). The correlation value of LQI ranges between 50 and 110 where 50 indicates the minimum value and 110 represents the maximum. Software converts the correlation value to the range 0-255:

$$\mathrm{LQI} = (\mathbf{CORR} - \mathbf{a}) * \mathbf{b} \tag{3}$$

Where,
CORR = correlation value
a and **b** are found empirically based on Packet Error Rate (PER) measurements as a function of CORR.

LQI is the preferred metric for the current work, rather than the RSSI metric used by Bocca et al. [19]. In ZigBee-compliant mesh network radios, the LQI is convenient to obtain from neighbour request packets as the instantaneous unidirectional link values are transmitted as the final byte of any message. By comparison, the RSSI value is more difficult to obtain simultaneously for all links at each sample time-point without an additional computational burden inherent in time-stamp synchronisation.

III. RESEARCH CHALLENGES AND GOALS

A. Design challenges

Smart environments have enabled computerised observation of human interaction. However using this acquired information as contextual information for the purpose of adapting the behaviour of an automated environment is less well researched and is the main reason for undertaking this research. The analysis of multiple targets provides information about social context and enables computer systems to track and anticipate human interaction. The latter is a non-trivial problem because human activity is situation dependent and not necessarily planned. Smart environments need to make use of this situational information in context in order to respond appropriately to human activity. "Context is key for interaction without distraction." [6]

B. Detecting human behaviour from multimodal observation

Brdiczka et al. [6] in their 2009 paper address the problem of learning and recognition of human behaviour models from multimodal observation in a smart home environment, similar to the University of Hertfordshire Robot House (UHRH). Their approach formed part of a framework for acquiring a high-level contextual data model for human behaviour in an augmented environment. In particular, their work focused on the automatic acquisition of information about social context and activity recognition from the analysis of the interactions between small groups of two or more individuals in real-time. Their multi-modal set-up comprised audio and video information. A 3-D video tracking system was used to create and track persons. A speech analyser determined if and when participants were speaking. Background environment noise was captured with an ambient sound detector. An individual role detector derived person-specific activities such as walking or interacting with an object frame by frame from 3-D tracker data (posture, speed and interaction distance). The association of audio stream data with each individual person identified by the 3-D tracker was coded by hand prior to commencing each recording. Several set-piece social situations were learned and detected using Hidden Markov Models (HMM) based on role and audio data. The authors propose a general framework methodology for the recognition and learning of the different components comprising a human behaviour model. The learning and detection was achieved in a two-part process involving first offline analysis (learning) followed by online detection of learned behaviour models.

C. Real-time object tracking and localisation

Real-time evaluation of video and audio streams is generally costly in terms of computing power. RTI in contrast uses multiple target tracking algorithms to generate real time images (every 13.3ms) of the change in the RF propagation field. The system is capable of running on a laptop having a 2.50GHz Intel$^{(R)}$Core^{TM} i5-2450P processor and 8GB of RAM memory [5]. The application of RTI techniques for multiple person tracking as an adjunct to the methodology described in this section, may provide useful improvements both to the problem of multi-person situation recognition and to the online (real-time) detection problem. The RTI system initially developed by Wilson and Patwari [4] and later extended by Bocca et al. [5] provides a basis for the current research. Their work targeted using changes in the RSS of the links in WSN to localise and track multiple people or other targets in real time without needing them to carry or wear any electronic device. Their work represents an important step in showing that the application of methods informed by machine vision and adapted to radio tomography could be used to generate images of the changes in the propagation field as if they were frames of a video. Our current research seeks to build upon this base, and eventually to extend it to use the sensor fusion method initially developed by Brdiczka et al. [6]. Their work was targeted at learning and recognition of human behaviour models from multimodal observation in a smart home environment. This work, however, was limited in two respects. Firstly, it relied upon a computationally expensive 3-D video tracking system requiring extensive offline (and therefore non real-time) processing in order to visualise human activities and to create and to track entities (people) in a scene. Secondly, because the detection of group dynamics and group formation, which is necessary for group situation recognition in (informal) real settings, remains an open issue within 3-D video tracking technology. This requires studying the use of RTI as part of a framework for acquiring a high-level contextual model for human behaviour in an augmented environment. It is envisaged that ROS will be utilised as a framework to implement processing nodes, which can process and integrate data acquired from multiple sensor types. Additionally, if evaluation metric testing between 3-D video tracking and RTI suggests that RTI is at least as reliable as the current video sensors, it may obviate the need for video sensors in future multi-modal observation studies.

IV. Initial Studies

We constructed a minimal full mesh network comprising 5 nodes using XBee Series 2 radio modules running the ZigBee protocol firmware [20]. The individual Router nodes were labelled 'A' to 'D' respectively and the network coordinator node 'BB' Power supply is via a USB connector. Transmit power was set to minimum for all nodes. Initial simple, single person experiments were performed in a room at the University of Hertfordshire. We deployed 5 sensors spaced at approximately 2 meter intervals apart, each at a height of about 1 meter forming 3 sides of a rectangle, with the fourth side 'open'. The thick arrow indicates 'open' side walk path direction. Nodes 'A' and 'BB' not pictured but mirror positioned to 'C' and 'D' respectively. (Figure 1).

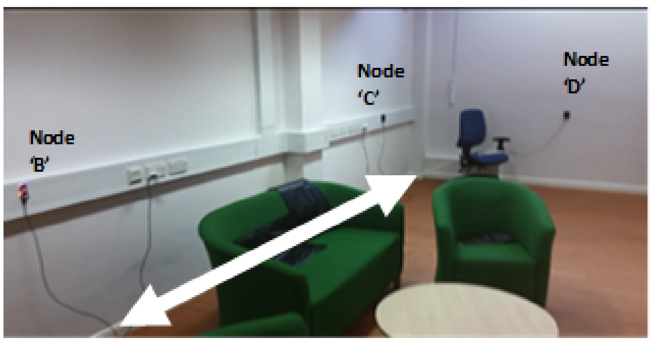

Figure 1. Experimental setup: nodes 'B', 'C' and 'D' are shown.

Evaluation was performed by walking along the length of the open side. Two walks were performed: Walk 'A' (walk away-turn-walk back) and Walk 'B' (walk away-turn then pause for 10seconds-walk back). The system collected time-series data sampled at the default rate of approximately 2 s^{-1}. Fluctuating LQI data generated from static, rotational and dynamic walk phases was captured (Figs. 2 & 3). In the Walk 'A' graph at Figure 2, the three individual phases of the motion are clearly identifiable: the pre-motion phase commences with a steady state, empty room flat line signal with no discernible noise and LQI of 255 representing the maximum value. LQI values then fall during the 'walk away' phase, bottom out during the 'turn' phase, rising again during the 'walk back' phase, finally returning to the maximum value and steady state. Data from other nodes has been omitted for visual clarity. The Walk 'B' graph at Figure 3 commences in similar fashion to the preceding graph. However the three individual phases of the motion are less clearly identifiable this time and there is less symmetry between the 'walk away' and 'walk back' phases. LQI values initially rise and return to roughly pre-motion values during the quiescent 'turn, pause' phase. During the 'walk back' phase, there is a brief dip followed by a gradual return to pre-motion values before finally returning to the maximum value and steady state. Again, data from other nodes has been omitted for visual clarity. These early results

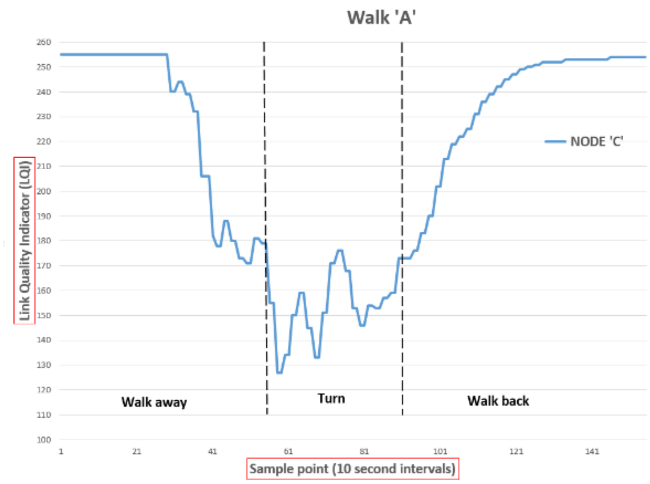

Figure 2. Walk 'A' LQI fluctuation for Node 'C'.

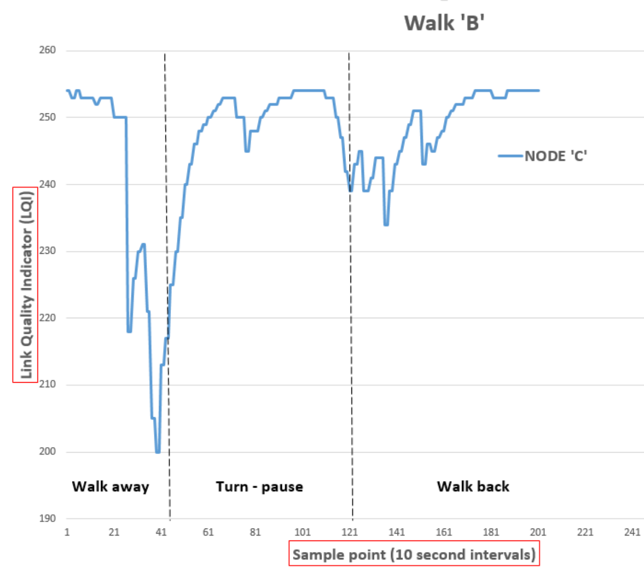

Figure 3. Walk 'B' LQI fluctuation for Node 'C'.

are promising and suggest that the use of the LQI metric is adequately responsive to differentiate characteristic phases of linear motion, rotational motion and no motion. Further, visual analysis of the graphs derived from the sensor data support the idea that specific activities produce uniquely identifiable patterns which may be classified by machine learning techniques.

V. Planned Studies

The next stage of research involves undertaking formally specified human motion studies which will be undertaken to implement basic algorithms already developed by others. The initial smart environment to develop and test the WSN for human activity detection will be deployed in the UHRH [21]. The UHRH is dedicated to Human-Robot Interaction (HRI) research in an ecologically realistic, domestic environment. It has the appearance of an ordinary British suburban, semi-detached house in a quiet residential street, with four fully-furnished bedrooms and a sizeable garden (see Figure

4). The UHRH is also inhabited by different robots designed for robot companion research. It also has a large number of embedded sensors, most connect via a WSN, allowing the recording of data from a range of different user activities.

A. Scaled WSN deployment

Initially, the number of nodes in the network will be increased from 5 to 8 and deployment will be limited to the 'living area' of the UHRH in order to collect basic data on a restricted set of activities. Later, in order to extend the sensor area coverage to include additional areas with different ADL, we intend to extend the area covered by the network to include up to 20 nodes.

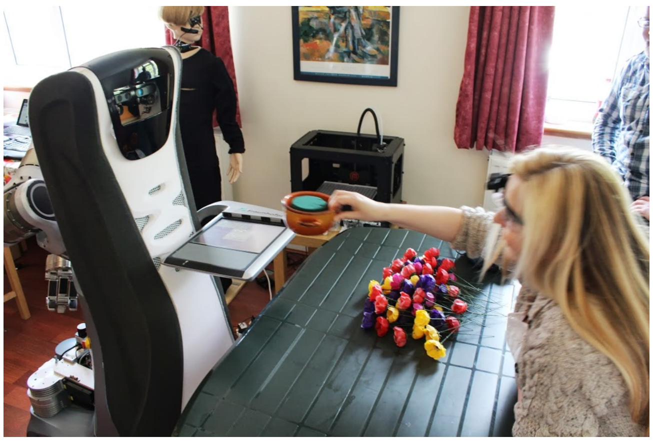

Figure 4. The University of Hertfordshire Robot House showing an HRI experiment with a Care-O-Bot 3 robot.

B. Input data

The input data can be conceptualised as a sequence of vectors mainly consisting of binary sensor data from the simple sensors (reed switches, pressure mats, water flow etc.) and more complex data structures for the RTI, 3-D video and audio streams.

C. RTI data processing pipeline

Following LQI data capture, digital signal processing techniques may be applied to form radio tomographic images in real-time according to the methodology of Bocca et al. [5] in a five-stage pipeline: (i) image estimation, (ii) image denoising, (iii) cluster heads selection, (iv) tracks confirmation and deletion, (v) target tracking.

VI. Conclusion and Future Work

Previous research at the UHRH has been undertaken on the design and implementation of a low-cost, resource-efficient activity recognition system that can detect ADL [22]. Following correlation with existing activity recognition collected from previously published RH studies, we intend to fuse data from existing sources/sensors in the UHRH with the RTI data based on the method developed by Brdiczka et al. [6], but using RTI data both separately and fused with 3D Tracker data. This will permit us to compare and contrast the technical performance of the two radio and optical imaging systems. We have demonstrated that we have obtained data from the ZigBee WSN, which has the potential to detect human movements. The WSN has been constructed from standard low-cost components of the type already used to connect sensors to UHRH systems etc. This raw data capture represents the essential first stage prior to implementing the RTI data processing pipeline methodology described by Bocca et al. and summarised at Section 5 above. Further, we have modified the approach taken by Bocca et al. and exploited the availability of the LQI metric in order to attempt an improvement in the reliability of the raw WSN data in an otherwise noisy 2.4 GHz environment (see Section 2 above for a technical discussion of the RSSI/LQI metrics). Graphical analysis of the initial data appears to demonstrate stable waveforms which do fluctuate appropriately in response to motion but are otherwise unperturbed (flat line, LQI value close to 255). In the next stage of research we plan to test the stability of the LQI sensor data in the noisy UHRH environment. There are several areas to which this research intends to make a contribution, namely HCI, Human-Robot Interaction (HRI) and the application of artificial intelligence (AI). The works of Patwari and Bocca have shown that RTI as a localisation and tracking technology can be used successfully to enable accurate real-time multiple target tracking with RF sensor networks. Concomitantly, the work of Brdiczka has shown that although a 3-D video tracking system is capable of creating and tracking entities (persons) in a smart environment, this is achieved not only at a substantially higher capital and computational cost than RTI, but also fails to adequately address the issue of the detection of group dynamics and group formation, which is necessary for group situation recognition. The proposed RTI methods aimed at circumventing the performance problems of 3-D video tracking systems have been shown to be successful in other tracking and localisation situations at reducing computation and memory costs.

The major unknown is to what extent RTI is capable of supplanting current optical data acquisition technologies at the machine learning level. A widely used technique for the analysis of time series data typically involves the use of feed-forward Artificial Neural Networks (ANN) employing a sliding window technique applied over the input sequence. However, before approaching the challenges of collecting time series data and subsequent processing via an appropriately selected ANN, there is a requirement to identify the optimal sample rate, embedding dimension and size of the input window [23]. In our approach to the problem of recognising activities we will consider implementing a real-time activity recognition digital signal processing (DSP) pipeline inspired by the methodology of [24]. Broadly, the pipeline architecture is envisioned in five principal stages. In the first stage raw LQI data is acquired from the WSN. Next, an aggregation step first loads the acquired live data and then initiates the downsampling, filtering and segmenting operations. Live LQI data may be written to a structured text file which may be conveniently parsed and loaded. In the third stage, windows of interest are identified from the loaded structured data by running a peak detection process. The windows of interest are slices of the LQI data corresponding to motion. Features are then extracted from the windows of interest which are then used to describe particular forms of

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motion (i.e. specific types of activities). In the penultimate stage, these features of interest are employed to train a recognition model for the movements detected and input. It is intended to generate a number of recognition models by exposing the data to differing classifiers in order to ascertain the optimal classifier for this time series motion data. Examples of potentially suitable classifier algorithms which are currently under consideration include Support Vector Machines, K-Nearest Neighbours, Decision Trees, Random Forest and Growing Neural Gas. In the final pipeline stage classification and validation operations will use classifiers and the dataset to perform cross-validation. Initially we intend to perform model training and classification offline by decomposing the dataset into a training set and a test set. The training set is fed into the various classifiers. The accuracy of each of the classifiers may be evaluated by comparing the classifier output predictions with the ground truth represented by the test set data.

We intend to use the Python programming language to initially implement all of the five stages of the pipeline described above. Python provides a number of excellent mature packages and libraries for DSP and machine learning including NumPy [25] and scikit-learn [26]. In the longer term, it would be desirable to develop the capability for our system to avoid the offline feature extraction and classifier training phase. In this respect the use of unsupervised learning of deep belief networks (Deep Learning) for generative pre-training of stacked Restricted Boltzmann Machines followed by supervised fine-tuning may be of interest. The Theano Python Library [27] offers tight integration with NumPy and significant performance gains through transparent use of a GPU.

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