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# Acknowledgements

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# Abstract

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# Chapter 1 - Introduction

## 1.1 Human Activity Recognition

Human activity recognition (HAR) is the term coined to define an ability to interpret a gesture or motion of the human body, and from this make a determination of the human activity or action being performed [1]. Recognizing a human’s activity, automatically, has become a significant problem in ubiquitous computing, human-computer interaction and human behavioural analysis [2]. Three scientific research contexts HAR finds itself an important component of are: surveillance, healthcare and human computer interaction [1].

### 1.1.1 Applications of HAR

**Surveillance**

HAR has been adopted in surveillance systems at public places, i.e. airports, banks, etc [1]. The findings in [3] confirm that proposed approaches are able to recognize ongoing human-human interactions at the earlier stage [1]. Furthermore, Legion: AR, a system proposed by [4], supplements existing recognition systems with on-demand, real-time activity identification to produce robust, deployable activity recognition [1].

**Healthcare**

The literature indicates that HAR has so far been employed in healthcare systems introduced in hospitals, rehabilitation centres, and even in residential environments [1]. HAR has extraordinary potential within the healthcare sector with a wide range of applications already seen today and is of particular use for aiding the elderly and vulnerable of society. By monitoring the activities of elderly people cared for in rehabilitation centres, HAR can be an effective way of monitoring chronic diseases as well as aiding disease prevention [1]. HAR is also utilised for monitoring patients at home to measure aspects of daily living such as energy expenditure to assist obesity prevention, treatment [5] and lifelogging [1]. Another use case of HAR is its application in monitoring stereotypical motion conditions suffered by children with Autism Spectrum Disorder (ASD) [6]. HAR can also be used for monitoring other behaviours such as those derived from abnormal conditions in cardiac patients [7], and the detection of early signs of illness [8], providing clinicians with an alarm mechanism for early intervention. More healthcare related HAR like fall detection is demonstrated by [9].

**Human Computer Interaction**

The human computer interaction field has seen the most well-known introductions of HAR, being adopted by gaming and exergaming such as Kinect and the Nintendo Wii [1]. The gestures and movements recognized through HAR are used by the machine to carry out specific tasks. HAR is also used in full-body motion-based games for older adults with neurological injury [1].

## 1.2 Types of HAR

There are two main types of HAR: video-based and sensor-based HAR [10]. More specifically, the sensing technologies used in HAR can be classified into the following three categories: RGB camera-based, depth sensor-based and wearable sensor-based [1]. These sensing technologies are discussed further in chapter two. The following figure illustrates the general structure of a HAR system for any of these sensing technologies:

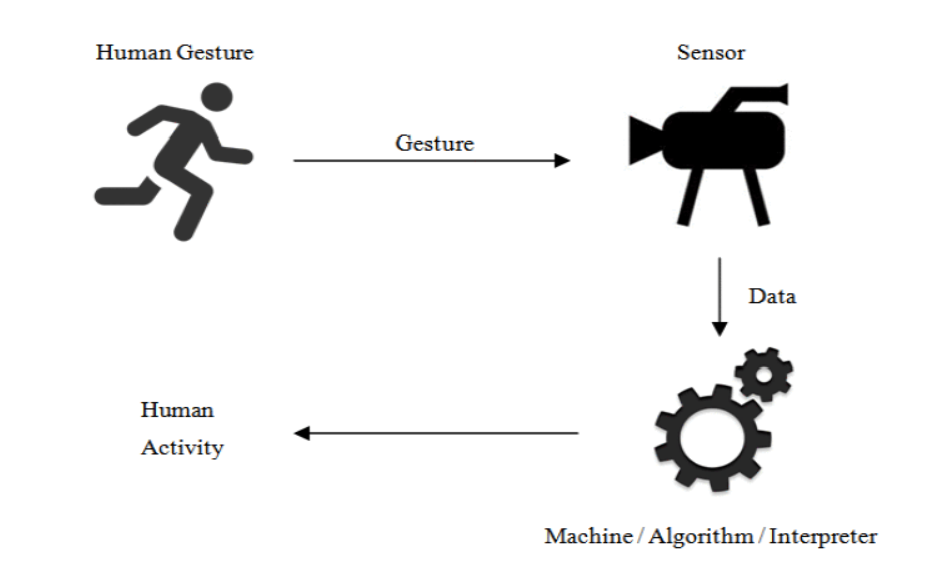


Figure 1: Structure of HAR system

Due to the rapid advancements in ubiquitous computing and the growth in concern for privacy protection, sensor-based HAR via wearable devices has seen itself rise in popularity. Because of this, and the reasons documented in chapter two, this project focuses on sensor-based HAR using wearable devices.

## 1.3 HAR: Machine Learning vs Deep Learning

HAR has most commonly been treated as a pattern recognition (PR) task, and to much avail. Machine learning algorithms such as the support vector machine have produced very satisfying results, most notably in controlled environments and where the volume of labelled data is low [10]. These machine learning methods do, however, rely on heuristic hand-crafted feature extraction which are limited to human domain knowledge. Hand-crafted features are hard to compute and difficult to scale [11], and therefore only shallow features can be learned using this type of approach [10]. In relation to HAR, training an accurate classifier is a particularly difficult task due to the high inter- and intra-class variability of human actions [11]. In other words, humans often perform different tasks differently to each other [11], which makes classification more difficult. Furthermore, using shallow, hand-crafted features reduces the performance of unsupervised learning methods [10]. Therefore, it is clear there are limited classification accuracies and model generalization available to the conventional pattern recognition approaches associated with the HAR problem [10].

The recent surge of pervasive computing has brought with it a rapid development and advancement of deep learning, achieving real success in a variety of domains [12]. In contrast to the conventional PR methods, deep learning is capable of learning high level features which are far more meaningful than the shallow features designed manually in conventional PR methods [10]. Convolutional neural networks (CNNs) have become very popular for their high accuracy in image classification [12]. By training a CNN, feature extraction and classification are combined into an encapsulated, end-to-end approach [11]. With respect to wearable-sensor based HAR, the features extracted through non-linear transformations are learned directly from the raw data, being more discriminative between the different human activity classes than those crafted in PR methods [11]. A drawback to deep learning, however, is its necessity for large amounts of labelled data to train a deep network. Although there are now many publicly available datasets particularly in the domain of object recognition, classification, detection and captioning such as ImageNet and MS-COCO, alternative tasks with a more specific scope may struggle to find labelled datasets on which to train their networks.

This report is structured as follows. Chapter two discusses the three different sensing technologies used in HAR detailing the advantages and disadvantages to each. Chapter two also covers some of the most common approaches to the HAR problem in the domain of time-series data generated from wearable sensors, and depicts the challenges faced by this domain of HAR and the suitability of CNNs for time-series data. Chapter two finally defines the problem being addressed by this project, which experiments with different adaptations to time-series data input to a suitable CNN architecture. Chapter three details the dataset used and describes the baseline approach taken by this project to the HAR problem. It then also details the design of the experiments, which attempt to improve upon the results obtained by the baseline approach. Chapter four is dedicated to the implementation details of this project, the results of which are discussed in chapter five. Chapter six is a piece about the ethics which are adhered to by this project. Chapter seven then draws some conclusions on the work documented by this project and discusses possible future work.

# Chapter 2 - Technical Background & Literature Review

## 2.1 Sensing Technologies

In order to choose a suitable sensing technology on which to design a HAR system, it is useful to discuss each of them and their pros and cons. The following three sensing technologies are discussed below: RGB video, depth sensors, wearable sensors.

### 2.1.1 RGB Video

Video-based HAR accepts videos/images capturing human motion as the input. Where the

camera is attached to the environment, the HAR system processes the image sequences using supervised learning. This involves the previous trainings of a system prior to its application [1]. This training stage consists of feeding image sequences along with the names of the human activity performed in those images into the system [1]. Feature extraction and classification are central components to the conventional HAR systems seen using this sensing technology [1] [\*13,48\*]. The RGB camera has been less preferred to other sensing technologies in the research of HAR [1]. There are a few reasons for this. Firstly, its ability to capture human motion in 3D space is limited [1] [\*39\*]. The performance of a real time HAR system may also suffer due to the high computational cost in the machine processing required to extract human movements from an image [1] [\*28\*] [\*5\*]. The biggest concern, however, regarding the employment of RGB camera data by a HAR system is the issue of privacy, i.e. users of such a system may not be comfortable with consenting to being recorded at all times [1].

### 2.1.2 Depth Sensor

A depth sensor can be referred to as an infrared sensor [1] [\*49\*]. This sends an infrared beam into a scene and recaptures it using the infrared sensor. The depth of an object can be calculated using the distance travelled by the beam [1]. Microsoft’s Kinect sensor is commonly employed as a depth sensor in HAR, according to reviews in [1] [\*33\*]. The Microsoft Kinect sensor is capable of detecting twenty human body joints using a real-world coordinate system [1] [\*40\*], which makes it very suitable for use in the classification of human movements. The literature is adamant that depth sensors are an improvement upon the RGB camera as a sensing technology [1]. The low cost of depth sensors has contributed to a rise in its popularity as a sensing technology for HAR [1] [\*19,20,27,37,39\*]. So too has its high sampling rate and capability of combining visual and depth information [1] [\*10\*]. Furthermore, the recognition processes appear to be far less expensive in comparison to those derived under RGB camera data [1] [\*10\*]. This said, depth sensors have so far been unable to solve the limitation of sensor viewpoint [1] [\*30\*] and sensor obstruction faced by the RGB camera [1][\*39\*].

### 2.1.3 Wearable Sensor

HAR via the use of wearable sensors requires only the subject wearing single or multiple wearables on their body [1]. The sensors typically found in these wearables are 3-dimensional accelerometer, gyroscope and magnetometers as well as temperature sensors. The emergence of wearables from smartphones (most smartphones now come with an accelerometer, gyroscope and magnetometer) to fitbits has opened many avenues for HAR. Wearables can also overcome the barriers of limited sensor viewpoint and sensor obstruction already discussed for RGB cameras and depth sensors. Additionally, wearables have the potential to act as a non-obtrusive [1] [\*26\*] solution to HAR as they have already proven to be effective in monitoring other aspects of daily living without infringing on the user’s quality of daily living. Further advantages of wearable sensors are their low monetary cost and high power efficiency [1] [\*46\*]. There are still some challenges facing wearable sensors, however. The accuracy of activity recognition using a wearable sensor may not be sufficient as current wearable sensor-based HAR systems require subjects to wear multiple sensors across different body parts [11] [1][\*23\*]. This is undoubtedly a sub-optimal solution to HAR as it is quite inconvenient and mildly intrusive for a subject to be required to wear multiple sensors across different body parts.

## 2.3 Sensor Modalities

Most HAR approaches work with just one specific type of sensor only. [10](Chavarriaga et al., 2013) suggests that we classify the sensor modalities into the following categories: *body-worn sensors, object sensors, ambient sensors.* These sensor modalities are further detailed below:

**Body-worn Sensor**

The body-worn sensor is of the most commonly used sensor modalities in HAR. As their name suggests, these sensors are most often worn by the user and include accelerometers, gyroscopes and magnetometers. These sensors are widely distributed throughout ubiquitous computing and are now very often found in watches, smart phones, bands, helmets and glasses. Body-worn sensors are very frequently used for deep learning based HAR [2] [11] [13] [14]. This related work shows that body-worn sensors are primarily adopted for recognizing activities of daily living (ADL) and sport. One notable point regarding the use of body-worn sensors in deep learning based HAR is that it is the original signal produced by the sensors that is used as the input to the network, as opposed to the approach of traditional machine learning methods where the inputs are statistical/frequency features extracted from the motion data.

**Object Sensor**

Object sensors are different to body-worn sensors in that they infer human activity by detecting the movement of a certain object [10](Chavarriagaetal.,2013). Therefore, object sensors are placed on specific objects to detect their movement. For example, the activity of drinking water can be detected by placing an accelerometer on a cup, [10]. Radio frequency identifier (RFID) tags are often used and mainly employed in smart homes [10] (Vepakomma et al., 2015; Yang et al., 2015; Fang and Hu, 2014) and medical facilities [10] (Li et al., 2016b; Wang et al., 2016a). RFID tags are used as they can produce more fine-grained information aiding in the recognition of more complex activities [10]. Object sensors are not as popular as body-worn sensors for HAR as they are difficult to deploy in real-world environments, however, there is an emergence of using object sensors combined with other types for the recognition of more complex activities [10] (Yang, 2009).

**Ambient Sensor**

In contrast to object sensors which measure an object’s movement, ambient sensors attempt to capture changes in the environments. Human activity is inferred by capturing the interaction between humans and the environment. Radar, pressure sensors, sound sensors, and temperature sensors are all different examples of ambient sensors. The work with ambient sensors indicates they are usually embedded in users’ smart environment (smart home) and are used to recognize activities of daily living and hand gestures [10] (Lane et al., 2015; Wang et al., 2016a; Kim and Toomajian, 2016). Like object sensors, the deployment of ambient sensors is not easy and so they are often less preferred to other sensor types. Another drawback to ambient sensors is that they are very easily affected by the environment, and therefore, only specific types of activities are accurately inferable by ambient sensors.

**Hybrid Sensor**

The combination of sensor types has been shown to potentially improve the accuracy in HAR. Ambient sensors used alongside object sensors are advantageous as they provide information on object movements as well as the state of the environment. In [10] (Vepakomma et al., 2015), a smart home environment is designed in which a wide range of complex and fine-grained activities of multiple occupants are recognizable via the use of body-worn, object and ambient sensors. It is clear that using multiple sensor modalities can yield superior information of human activities. The work also shows that it is a deployable solution to HAR in certain environments like smart homes.

## 2.4 CNNs and HAR

Convolutional Neural Networks have been used extensively in the field of computer vision for their effective feature extraction and pattern recognition abilities. They have been widely adopted by deep learning and have produced very promising results in image classification, speech recognition and text analysis [10]. CNNs are of particular use in image classification as convolution leverages three important ideas: sparse interactions, parameter sharing and equivariant representations [15] [\*23\*], [datadriveninvestor?]. With these properties, CNNs can extract smaller features of greater significance, whilst at the same time reducing the storage requirements compared to those more densely connected neural networks [15]. In addition to this, the depth and breadth of convolutions are adjustable, making it easier to train CNNs compared to alternative feedforward neural networks [15]. CNNs do, however, raise the concern of overfitting the training set, particularly in image recognition. If overfitting has occurred, it means that the CNN is also learning the obsolete background features of the training images, aiding the classification accuracy of the training set [15]. This is not desirable as it means that the trained model will not generalise well, i.e. it has failed to capture the more general characteristics of the training set and so, on unseen data, the model will not produce a classification accuracy close to that found on the training set.

When used for the classification of time-series data, like in HAR, CNNs have two advantages over other models: local dependency and scale invariance [10], [14]. Local dependency refers to the correlation between nearby signals [10]. Scales invariance means the output is not sensitive to a variance in paces or frequencies in the input. When using CNNs as a solution to the HAR problem, the concepts of *input adaptation, pooling* and *weight sharing* must be considered [10].

### 2.4.1 Input Adaptation for CNNs

The sensors used in HAR, obviously, do not produce image data. These sensors produce time-series readings. The most commonly gathered data in wearable sensor-based HAR are accelerometer, gyroscope and magnetometer time-series signals. More specifically, these are 3-axial (x, y and z direction) 1D readings along the temporal dimension [10]. These readings must be adapted first before a CNN can be applied to them. The inputs must first be adapted to form a *virtual image* [10]. There are two ways of achieving this: *data-driven* and *model-driven*.

* **Data-driven:** This approach is straightforward and easy to implement. Each dimension is treated as a channel on which a 1D convolution is performed, i.e. each 1D sensor is treated as a 1D image [10]. Although uncomplicated, this approach does have a drawback: it does not account for dependencies between dimensions and sensors, which may impact performance [10].
* **Model-driven:** This approach looks to apply a 2D convolution, and so resizes the inputs into a 2D virtual image [10]. The advantage of this approach is that it can incorporate the temporal dependencies between sensors [10]. This conversion from time-series to image data is, however, a non-trivial task and requires domain knowledge [10].

### 2.4.2 Pooling

Pooling is often paired with convolution in CNNs. The most common types of pooling are max or average pooling. Convolution is so often combined with pooling operations to avoid overfitting [10]. Each time an input image is pooled, the image size is reduced (usually to half the size). Therefore, pooling helps to reduce the training time on large training sets as it reduces the number of parameters to be tuned [10] (bengio, 2013).

### 2.4.3 Weight Sharing

## 2.6 Common Approaches to HAR

(Few take a machine vision approach – only found one paper)

Many different approaches have been taken to the HAR problem and many works tackle HAR from different angles. [16] explores, compares and contrasts the state-of-the-art deep learning methods for HAR using wearable sensors regarding performance. [16] gives great insights into the suitability of each model with respect to specific tasks in HAR. The three main deep learning architectures assessed in [16] are Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs) and regular Deep Feed-Forward Neural Networks (DNNs). It is observed from [16] RNNs that outperform CNNs significantly on activities that are short in duration but have a natural ordering. It is clear that the performance of a recurrent approach benefits largely from its ability to contextualise observations across long periods of time. It is, however, recommended that CNNs are used for more prolonged and repetitive activities such as walking/running. Although some RNNs were found to perform similarly to or even better than CNNs in this environment, the *average* performance of CNNs in this domain suggest a higher likelihood that the practitioner finds a suitable configuration using a CNN architecture. Furthermore, through the experiments in [16] it is recommended to explore different learning rates prior to optimizing the network architecture. This is due to the experiments in [16] demonstrating that a change in learning parameters has the largest impact on performance. The work with DNNs in [16] indicate that they require a significant investment in the exploration of parameters, showing a notable spread between peak and median performance. It is concluded from [16] that the use of CNNs or RNNs are a more sophisticated approach to DNNs, showing a smaller spread in performance and a higher likelihood of finding a configuration that works sufficiently, particularly in the case of CNNs.

[2] focuses on the HAR problem where the inputs are multi-channel time-series measurements gathered from inertial measurement units worn on different parts of the body, and the outputs are predefined human activities, e.g. walking, running, sitting etc. The architecture used by [2] is a deep CNN, automating feature learning from the raw inputs. As so often used in HAR, labelling the inputs via supervised learning produces learned features with more discriminative power [2]. [2] uses benchmark datasets like the Opportunity Activity Recognition dataset and Hand Gesture dataset to verify that the unique advantages to CNNs propel their CNN architecture to outperform other state-of-the-art machine learning solutions to HAR such as SVM, KNN, Means and Variance, and Deep Belief Network.

Similar to [2], [11] focuses on the HAR problem where the inputs are multi-channel time-series measurements. A novel CNN is proposed by [11] in which the network used processes the sequence measurements from different body-worn devices separately. This follows the idea of a wider rather than a deeper network, where the architecture consists of multiple branches, each processing the data from one specific inertial device only. This is done to provide some robustness against the inertial devices being asynchronous or having slightly different characteristics. With each branch providing an IMU-specific, intermediate representation of the data, a global representation is found via fully connected layers. 1D temporal convolutions and pooling operations are performed on the input’s sequences. [11] evaluates the proposed architecture on three benchmark datasets including the Opportunity Activity Recognition and Pamap2 datasets, outperforming the state-of-the-art. [11] advises that the capabilities of CNNs are improved by applying convolutions per sensor and per body worn device.

[17] proposes the use of 2D kernels in both convolutional and pooling layers to capture spatial dependency over sensors in addition to local dependency over time (already provided by the temporal convolution). [17] demonstrates a high performance of this multi-modal CNN, compared to state-of-the-art methods by experimenting on benchmark datasets.

As in [17], [18] applies 2D convolution and pooling to capture both spatial and local dependency. However, it is not the raw time-series data which is passed into the network. [18] carries out pre-processing steps to adapt the time-series input sequences into a 2D virtual image. It first uses an algorithm to create an image of sensor channels where each sensor channel is placed either above or below all other sensor channels at least once. This is done to allow the deep CNN to extract hidden correlations between neighbouring signals. This generates a new signal image. The DFT of each channel in this signal image is found to generate a new activity image. The activity image is the input which is passed to the architecture. According to [18], this approach outperforms the state-of-the-art in terms of recognition accuracy and computational cost.

[19] presents CNNs for multi-modal data (multi-sensor, e.g. accelerometers and gyroscopes) where it introduces both partial weight sharing and full weight sharing to the CNN models in a manner that both modality-specific characteristics and common characteristics across modalities are learned from multi-modal data. The results in [19] indicate that weight sharing can improve the performance of a CNN.

[15] takes an alternative approach to HAR with the use of photoplethysmography sensor data gathered from wearable devices. [15] looks to simplify the wearable approach to HAR by experimenting with wrist-mounted optical sensing (used usually for heart rate determination) to see if it can provide data useful for activity recognition. In contrast to many of the papers discussed, [15] takes a machine vision approach to the HAR problem, using the plots of the optical signals to produce activity classifications. More specifically, [15] implements transfer learning to retrain the penultimate layer of a pretrained CNN, using time-series *images* of the photoplethysmography signals as the inputs to the network. [15] achieves an average accuracy of 75.8%, which is a competitive result, suggesting that the overall design of activity monitoring and classification systems could be simplified to wearables based on optical measurements only. However, implementing a design of optical sensor only in an activity classification system does lead to a trade off in classification performance.

As can be seen, there are many different approaches to the HAR problem, with many variations in architectures and how the data is represented. After a careful examination of the literature on HAR, it can be concluded that CNNs are the most effective network used in HAR to date. After an in-depth study of the literature surrounding HAR, this project takes the following form. Firstly, this project attempts to reimplement the architecture in [11] to establish a baseline approach to HAR. A benchmark dataset, Pamap2 [20] accessed at [21], as is used in [11] is used to implement and test this baseline approach. Once a working network is established and a model is successfully trained, where the inputs are multi-channel time-series measurements from inertial sensors, a machine vision approach is then taken. This project then explores the concept executed by [15], where plots of sensor signals are saved as images and are then passed as inputs to the network. In [15], just one optical signal is plotted, providing an average classification accuracy of 75.8%. This project applies a similar approach to inertial measurement data where multiple triaxial sensors are used. In theory, the approach taken by [15] should be enhanced where multiple signals are plotted, providing more information than just a single optical signal as in [15]. This project explores and compares different ways of plotting the data and how best to combine the data of multiple inertial sensors. It also experiments with different architectures and learning parameters in order to determine what set up is needed to best support this machine vision approach. The approach in [11] is chosen as the baseline approach for this project as the use of separate branches may provide flexibility when experimenting with different ways of passing the plots of multiple inertial devices to the network.

## 2.7 Modality Transformation

Modality transformation refers to the conversion of data from a source mode to a target mode [12].

# Chapter 3 - Design of Solutions

## 3.1 The Dataset

The dataset used by this project is freely available for academic research and has often been used as a benchmark dataset in HAR research [11], [1]. Of the public datasets available, the Pamap2 dataset has one of the highest sampling frequencies of 100 Hz, along with one of the highest number of samples, 2,844,868 [1]. It is also one of the few datasets with the luxury of having an accelerometer, gyroscope and magnetometer all in use, along with temperature sensors and a heart rate monitor.

### 3.1.1 Hardware Setup

For the measuring of the different activities of daily living performed in this dataset, three Colibri wireless inertial measurement units (IMUs) were used. The position of these IMUs on the body of each subject during the data collection was as follows:

* 1 IMU over the wrist of the dominant arm
* 1 IMU on the chest
* 1 IMU on the ankle of the dominant leg

The sampling frequency of the IMUs is 100 Hz.

In addition to the three IMUs, each subject also wore a heart-rate monitor, BM-CS5SR from BM innovations GmbH. The sampling rate of the heart rate monitor used is ~9 Hz.

Finally, a companion unit was used: Viliv S5 UMPC. This companion unit has an Intel Atom Z520 CPU (1.33 GHz) and 1 GB of RAM. The labelling of the different activities performed during the data collection was done via a GUI running on the Viliv.

### 3.1.2 Subject Information

A total of nine subjects participated in the collection of this dataset. Eight of the participants were male with just one female participant, and the age spread of the subjects at the time of the data collection was 27.22 ± 3.31 years. The subjects had a BMI of 25.11 ± 2.62 . The table below shows the relevant information of each subject:

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Subject ID | Sex | Age (years) | Height (cm) | Weight (kg) | Resting HR (bpm) | Max HR (bpm) | Dominant Hand |
| 101 | male | 27 | 182 | 83 | 75 | 193 | right |
| 102 | female | 25 | 169 | 78 | 74 | 195 | right |
| 103 | male | 31 | 187 | 92 | 68 | 189 | right |
| 104 | male | 24 | 194 | 95 | 58 | 196 | right |
| 105 | male | 26 | 180 | 73 | 70 | 194 | right |
| 106 | male | 26 | 183 | 69 | 60 | 194 | right |
| 107 | male | 23 | 173 | 86 | 60 | 197 | right |
| 108 | male | 32 | 179 | 87 | 66 | 188 | left |
| 109 | male | 31 | 168 | 65 | 54 | 189 | right |

### 3.1.3 Data Collection Activity Protocol

Each subject followed a protocol containing twelve different activities of daily living. In addition to this, a list of optional, additional activities was given to the subjects. From the list of optional activities, a total of 6 different activities were performed by some of the subjects in addition to the protocol. The list of optional activities contained a wider range of activities from household and everyday activities to sport activities. Below shows a list of the activities along with their label:

|  |  |
| --- | --- |
| Activity ID: | Activity |
| 1 | Lying |
| 2 | Sitting |
| 3 | Standing |
| 4 | Walking |
| 5 | Running |
| 6 | Cycling |
| 7 | Nordic walking |
| 9 | Watching TV |
| 10 | Computer work |
| 11 | Car driving |
| 12 | Ascending stairs |
| 13 | Descending stairs |
| 16 | Vacuum cleaning |
| 17 | Ironing |
| 18 | Folding laundry |
| 19 | House cleaning |
| 20 | Playing soccer |
| 24 | Rope jumping |
| 0 | Other (transient activities) |

The dataset documentation instructs that any data labelled with an ID of 0 should be ignored in any analysis. This data is that which was collected when the subject was transitioning from one activity to another, and so is not indicative of any specific activity.

### 3.1.4 The Collected Data

In the actual collection of the data, some data was lost. This is due to two main causes: data dropping and problems with the hardware setup. Data dropping may have occurred from using wireless sensors. It is also important to note that the “real” sampling frequency of the IMUs was 99.63 Hz, 99.89 Hz and 99.65 Hz for the hand, chest and ankle IMU respectively.

In total, over ten hours of data was collected, from which almost eight hours is representative and labelled as one of the 18 activities performed during the data collection. The below histogram shows the distribution of activities across all subjects with respect to time in seconds:

### 3.1.5 Data Format

The synchronized and labelled raw data from all sensors (3 IMUs and the HR-monitor) is merged together into one single file per subject and per session (protocol/optional). These data (.dat) files are made available at [21]. These data files each have 54 columns per row. The data under each column is summarised below:

* 1 timestamp
* 2 activity ID (label)
* 3 heart rate (bpm)
* 4-20 IMU hand
* 21-37 IMU chest
* 38-54 IMU ankle

The data under each column of the IMU sensory data is summarised below:

* 1 temperature (°C)
* 2-4 3D-acceleration data (), scale: ±16g, resolution: 13-bit
* 5-7 3D-acceleration data (), scale: ±6g, resolution: 13-bit
* 8-10 3D-gyroscope data (rad/s)
* 11-13 3D-magnetometer data (µT)
* 14-17 orientation (invalid)

The dataset documentation informs that the orientation data collected is invalid. All missing sensory data due to wireless data dropping are replaced with NaN in the data files. Because the HR-monitor has a much lower sampling frequency of 9 Hz compared to the sampling frequency of the IMUs (100 Hz), there are far less HR data values recorded. The missing HR values are also filled in with NaN in the data files.

Finally, the Pamap2 dataset documentation also advises that the second accelerometer is not calibrated exactly with the first one. Due to the high impacts of more strenuous activities like running where an acceleration exceeds 6g, the second accelerometer of scale ±6g sometimes gets saturated. Therefore, it is advised that the data of the first accelerometer with a scale of ±16g is used.

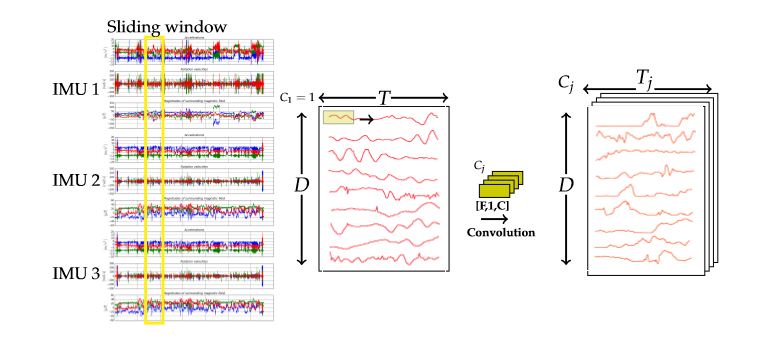
## 3.2 Baseline Approach

As mentioned, this project attempts to replicate the architecture designed by [11]. This architecture uses a convolutional neural network (CNN). A CNN is a hierarchical structure which combines convolutional operations that use learnable filters and non-linear activation functions with downsampling (pooling) operations and classifiers [11]. Different features are extracted at different layers of a CNN. CNNs are capable of extracting more abstract features by stacking convolutional layers and downsampling their outputs [11]. This way, CNNs can also remain invariant to distortions [11].

With HAR where the data is multichannel time-series measurements, the actual input to the CNN is a stack of segmented sequences of the different sensors used for some specific duration of time. Therefore, the input is a 2D matrix where each row corresponds to a single 1D sensor sequence and each column represents a single sample of data for each sensor. Therefore, the input is a 2D matrix of *T* measurements for each of the *D* sensors. As commonly used for time-series data, [11] uses a sliding window approach to generate these inputs.

### 3.2.1 Sliding Window

With a stacked sequence of *d* = 1, 2, …, D sensors, a sliding window of size *T* is moved forward along the sequences with some frame-shift, *s*, segmenting the input sequences [11]. These segmented sequence inputs are therefore of size [*T, D*] [11]. By ensuring a small value of s, multiple windows for even just a single activity can be extracted [11]. Furthermore, generating a large number of samples is important for training a CNN effectively [11]. The CNN’s inputs extracted using a sliding window approach is illustrated below:



As can be seen, a *virtual image* of the sensory data has now been generated using the sliding window technique.

### 3.2.2 Temporal Convolution and Pooling

The *virtual image* inputs can also be expressed as feature-map inputs to the convolutional layers. In CNNs, each convolutional layer convolves its feature-map inputs with *C* filters along the temporal axis [11]. Consider layer *i*. A single input to layer *i* is a feature-map of size [*T, D, C*] [11]. Now consider layer *j*, connected to layer *i* via a set of filters of size [*F, 1,* ] and biases [11]. A temporal convolution of each sensor d (1D) can be expressed by the following equation [11]:

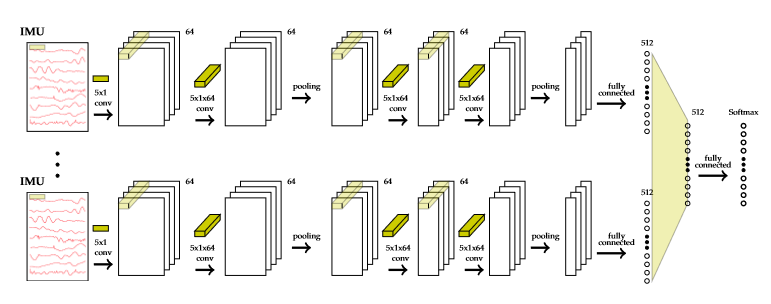
*σ* is the activation function. As can be deduced from the above equation, the filters are shared among all D sensors.

Pooling operations reduce the size of the feature-map with respect to the temporal axis. The most common pooling operation, max-pooling, is used by [11] to induce a temporal robustness. For a single channel *c*, a max-pooling operation between two layers, *i* and *j*, simply finds the maximum value among a set of p values. Where is the feature map input to pooling layer *i*, the max pooling operation can be expressed by the following equation:

### 3.2.2 The Architecture

**CNN-IMU Network**

The novel architecture proposed by [11] processes the time-series data of multiple IMUs separately. This is based on a sensor setup, demonstrated by the Pamap2 dataset, where the subject wears multiple IMUs at different locations around their body. [11] refers to this architecture as a CNN-IMU network, and is illustrated below:



As seen in figure xnumx, this architecture consists of parallel branches, one per IMU. Each branch contains *B* blocks, with each block having two stacked [5 x 1] temporal convolutions followed by a subsequent [2 x 1] max pooling operation. It uses temporal convolutional layers to locate temporal-local features in the inputs [11]. Fully-connected layers are implemented to connect the local features and generate a global representation of the data [11]. Each branch finishes with a fully connected layer [11]. These layers are processed simultaneously for each IMU to increase the descriptiveness of the network [11]. The use of separate branches for each IMU is also implemented to increase the robustness of the network to slightly asynchronous IMUs or IMUs having varying characteristics [11]. The network then combines the intermediate representations of each branch into a global representation of the data using a subsequent fully connected layer [11]. As this is a classification task where an input sequence segment can represent only one activity, a softmax classifier is used to generate probabilities for each class. [11] uses the cross-entropy loss between the estimated probabilities and the target label for training the model. Finally, dropout is also applied to all fully connected layers, apart from the classification layer. The number of neurons used per layer is *C* = 64 [11].

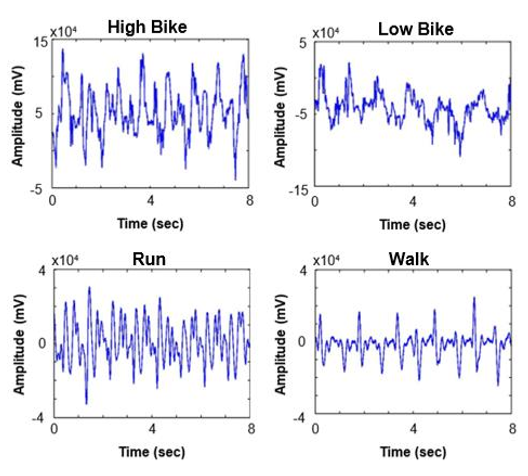
**CNN Baseline Network**

[11] also evaluates a slightly simpler CNN baseline network, which takes in a single virtual image of the sensory signals from *all* of the IMUs, not just a single IMU. This architecture is that which is more commonly seen in HAR [2], and can be thought of as the CNN-IMU architecture described above with just a single branch to process the data of all IMUs. Thus, this CNN baseline network consists of *B* blocks of two [5 x 1] temporal convolutions followed by a [2 x 1] max pooling operation, with three fully connected layers at the end.

This project replicates both architectures, CNN-IMU and CNN baseline, proposed in [11] as the baseline approach to this project. This project then experiments with modality transformation of the sensory data inputs, from a *virtual* 2D image of time-series measurements into an actual image. The design of these experiments is described below:

## 3.3 Experiment Design

This project then carries out three experiments where, following [15], a machine vision approach is taken. [15] designs its own data collection where photoplethysmography (PPG) recordings are taken from 8 subjects (3 male, 5 female), with a mean age of 26.5 years [15]. The PPG recordings are taken from the subjects during controlled exercises on a treadmill and exercise bike using a wrist-worn PPG sensor [15]. The four exercises performed in this data collection are: walking, running, low resistance cycling and high resistance cycling [15]. The signals gathered are then segmented into smaller 8-second (used in [\*18\*]) long time-series windows. Similar to the baseline approach of this project, a sliding window function is used to step through the data with a frame shift, *s*, of 2 seconds, each time saving a new plot of 8 seconds worth of the time-series PPG data. To clarify, it is a machine vision approach being taken here. Therefore, the input data created by [15] are actual images (saved as .jpg files) and not time-series vectors. [15] gives the following example for the plots of the PPG data for each of the four activities:



[15] uses the concept of transfer learning to retrain the penultimate layer of a pretrained CNN (a trained network for image classification). However, [15] advises that this approach may be a limitation to the potential classification accuracy of the system, suggesting that building a complete neural network from scratch could yield better results.

This project attempts to apply the same machine vision approach to the time series data gathered from multiple IMUs as seen in the Pamap2 dataset already described. Following the suggestion made by [15], this project then uses the input data to train a network from scratch, as opposed to using transfer learning. The CNN baseline and CNN-IMU architectures built for the baseline approach of this project are also utilised and experimented with using for this innovation. This project experiments with three specific machine vision approaches, detailed below.

### 3.3.1 Machine Vision Approach 1

### 3.3.2 Machine Vision Approach 2

This approach uses a CNN-IMU architecture, where there are separate branches for each of the IMUs and the HR-monitor. Therefore, there is a total of four branches. Due to there being only a single sensor channel for the HR-monitor, the single channel time-series data is passed in as the input to the first branch (branch for the HR-monitor). Another reason for this is the lower sampling rate of the HR-monitor in comparison to the IMUs. Because the sampling rate is roughly ten times lower than that of the IMUs, a plot of the HR-monitor data does not provide enough information to justify using plots of the HR-monitor data as inputs to the HR branch, particularly where the window size is chosen to fit the sampling rate of the IMUs.

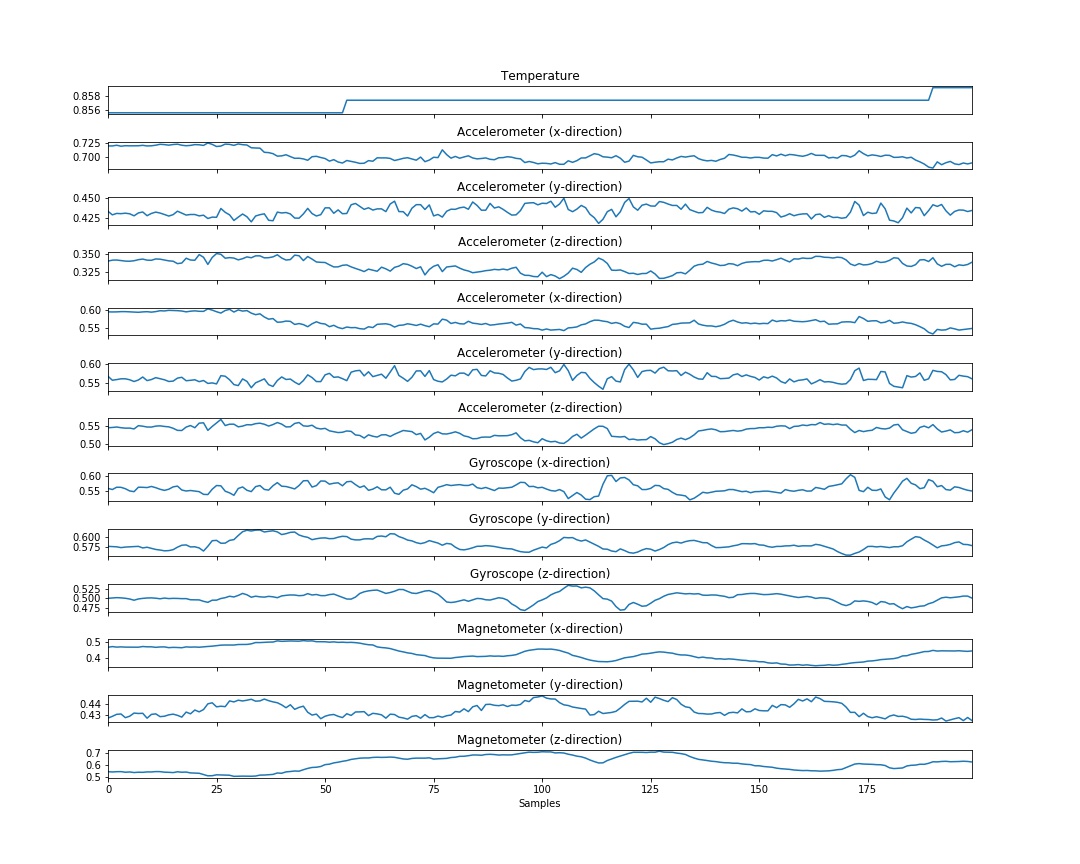
Just as in the baseline approach, a sliding window technique is used to generate the plots. This time, instead of generating a *virtual* image of size [*T, D*], where *T* is the window size and *D* is the number of sensor channels, an actual image is generated consisting of *D* subplots. Each subplot plots the time-series data of sensor channel *d* against time for some number of samples (window size) *T*.

Recall that each IMU consists of the following sensors:

* temperature (°C),
* 3D-accelerometer (), scale: ±16g, resolution: 13-bit,
* 3D-accelerometer (), scale: ±6g, resolution: 13-bit,
* 3D-gyroscope (rad/s),
* 3D-magnetometer (µT).

Although the dataset documentation advised that the accelerometer of scale ±6g gets slightly saturated for the more explosive activities which cause larger accelerations, this data is still used in both the baseline approach and experiments of this project. This is due to the fact that this data is used by [11], which acts as the benchmark for this project.

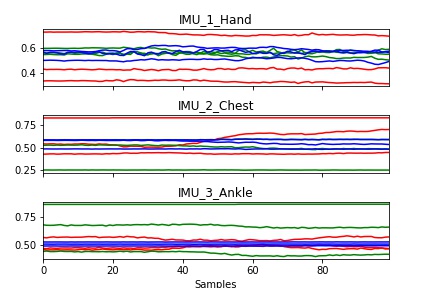
As can be seen, there are 13 sensor channels per IMU. This experiment adopts an approach where the finer fluctuations in all sensor signals must be represented by the image. Therefore, each image has 13 subplots, each with their own y-scale. This way, the behaviour of each signal with respect to time can be accurately represented. This can be seen more clearly in the below example, where a segment is plotted for T = 200 for one IMU:



The script which prints and saves these images ensures to remove all non-salient features such as axis labels, grid lines and ticks, legends etc. The image is saved as a 640 x 480 .jpg file.

### 3.3.3 Machine Vision Approach 3

This approach is different to the previous in three ways. Firstly, the sensor channels of all three IMUs are plotted on a single image. Secondly, all sensor channels of one IMU are plotted on a single subplot. Therefore, each image consists of three subplots, one per IMU. Finally, an RGB image is generated where plots of acceleration data are red, plots of gyroscope data are green, and the plots of magnetometer data are blue. The below image demonstrates this setup:



This approach attempts to account for dependencies between sensor signals. This does, however, lead to a trade off in the signal detail in the image. As can be seen in figure fxxxf, there is a loss in the finer detail of the sensor signals with respect to smaller fluctuations due to all sensor signals from a single IMU using the same y-axis.

Because all IMUs are represented on one image, a single branch is all that is needed for all three IMUs in the CNN-IMU architecture. An additional branch is needed to process the data from the HR-monitor. Just as is done in the previous machine vision approach, the single channel time-series data from the HR-monitor is passed in as the input to a separate branch in the CNN-IMU architecture.

# Chapter 4- Implementation and Testing

## 3.1 Dataset Design Protocol

## 3.2 Data Pre-Processing

## 3.3 Baseline Approach Implementation

## 3.4 Machine Vision Approach 1

## 3.5 Machine Vision Approach 2

## 3.6 Machine Vision Approach 3

# Chapter 5 - Results and Discussion

# Chapter 6 – Ethics

# Chapter 7 - Conclusions and Further ResearchReferences

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| [1] | O. C. Ann and L. B. Theng, “Human Activity Recognition: A Review,” in *2014 IEEE International Conference on Control System, Computing and Engineering (ICCSCE 2014)*, Batu Ferringhi, Malaysia, 28-30 Nov. 2014. |
| [2] | J. Bo Yang, M. N. Nguyen, P. P. San and X. K. S. Li Li, “Deep Convolutional Neural Networks On Multichannel Time Series For Human Activity Recognition,” in *Twenty-Fourth Joint Conference on Artificial Intelligence 2015*, 2015. |
| [3] | M. S. Ryoo, “Human activity prediction: Early recognition of ongoing activities from streaming videos,” in *IEEE International Conference on Computer Vision (ICCV)*, Barcelona, Spain, 2011. |
| [4] | W. S. Lasecki, Y. C. Song, H. Kautz and J. P. Bigham, “Real-time crowd labeling for deployable activity recognition,” in *2013 conference on Computer supported cooperative work-CSCW 13*, San Antonio, Texas, 2013. |
| [5] | E. S. Sazonov, G. Fulk, J. Hill, Y. Schutz and R. Browning, “Monitoring of posture allocations and activities by a shoe-based wearable sensor,” *IEEE Transactions on Biomedical Engineering,* vol. 58, no. 4, pp. 983-990, 2011. |
| [6] | G. Paragliola and A. Coronato, “Intelligent Monitoring of Stereotyped Motion Disorders in Case of Children with Autism,” in *2013 9th International Conference on Intelligent Environments - IEEE*, Athens, 2013. |
| [7] | E. Kańtoch and P. Augustyniak, “Human activity surveillance based on wearable body sensor network,” in *2012 Computing in Cardiology*, Krakow, 2012. |
| [8] | E. E. Stone and M. . Skubic, “Passive, in-home gait measurement using an inexpensive depth camera: Initial results,” , 2012. [Online]. Available: http://yadda.icm.edu.pl/yadda/element/bwmeta1.element.ieee-000006240383. [Accessed 21 3 2019]. |
| [9] | A. T. Nghiem, E. . Auvinet and J. . Meunier, “Head detection using Kinect camera and its application to fall detection,” , 2012. [Online]. Available: http://ieeexplore.ieee.org/document/6310538. [Accessed 21 3 2019]. |
| [10] | J. Wang, Y. Chen, S. Hao, X. Peng and L. Hu, “Deep Learning for Sensor-based Activity Recognition: A Survey,” *Pattern Recognition Letters, 2019 - Elsevier,* no. 119, pp. 3-11, 2019. |
| [11] | F. Moya Rueda, R. G. Grzeszick, G. A. Fink, S. Feldhorst and M. ten Hompel, “Convolutional Neural Networks for Human Activity Recognition Using Body-Worn Sensors,” *Informatics,* Vols. Informatics 2018, 5, 26, 2018. |
| [12] | M. Singh, V. Pondenkandath, B. Zhou, P. Lukowicz and M. Liwickit, “Transforming sensor data to the image domain for deep learning—An application to footstep detection,” in *2017 International Joint Conference on Neural Networks (IJCNN)*, Anchorage, AK, 2017. |
| [13] | J. Yang, M. Nguyen, P. San, X. Li and S. Krishnaswamy, “Deep convolutional neural networks on multichannel time series for human activity recognition,” in *Twenty-Fourth International Joint Conference on Artificial Intelligence*, 2015. |
| [14] | M. Zeng, L. Nguyen, B. Yu, O. Mengshoel, J. Zhu, P. Wu and J. Zhang, “Convolutional neural networks for human activity recognition using mobile sensors,” in *6th International Conference on Mobile Computing, Applications and Services*, 2014. |
| [15] | E. Brophy, J. Dominguez, Z. Wang and T. Ward, “A machine vision approach to human activity recognition using photoplethysmograph sensor data,” in *2018 29th Irish Signals and Systems Conference (ISSC)*, 2018. |
| [16] | N. Hammerla, S. Halloran and T. Plötz, “Deep, convolutional, and recurrent models for human activity recognition using wearables,” in *International Joint Conference on Artificial Intelligence (IJCAI)*, 2016. |
| [17] | S. Ha, J. Yun and S. Choi, “Multi-Modal Convolutional Neural Networks for Activity Recognition,” in *2015 IEEE International Conference on Systems, Man, and Cybernetics*, 2015. |
| [18] | W. Jiang and Z. Yin, “Human activity recognition using wearable sensors by deep convolutional neural networks,” in *23rd ACM international conference on Multimedia*, 2015. |
| [19] | S. Ha and S. Choi, “Convolutional neural networks for human activity recognition using multiple accelerometer and gyroscope sensors,” in *2016 International Joint Conference on Neural Networks (IJCNN)*, Vancouver, 2016. |
| [20] | A. Reiss and D. Stricker, “Introducing a New Benchmarked Dataset for Activity Monitoring,” in *The 16th IEEE International Symposium on Wearable Computers (ISWC)*, 2012. |
| [21] | “UCI Machine Learning Repository,” 2007. [Online]. Available: http://archive.ics.uci.edu/ml/datasets/pamap2+physical+activity+monitoring. [Accessed January 2019]. |

# Appendix 1

# Glossary