Profiling with Smart Meter Data in a Virtual Reality Setting

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***Abstract*— Visualising complex data facilitates a more comprehensive stage for conveying knowledge. Data-to-day, we are surrounded by data. Each one of us is also a regular creator of data. For example, even simply surfing the internet, and following links, generates information that is collated by the website owner. Similarly, the introduction of the smart meter has meant that we are now generators of data from using electivity and gas in our home. Organisations are finding increasingly more interesting ways to manipulate datasets such as this. For example, smart meter data is being increasingly used for predicting load balancing within the smart grid and for the development of remote healthcare monitoring services. It is clear that by visualising complex datasets, finding answers to complex questions in an understandable manner becomes possible. Yet, interpreting large datasets using virtual reality is a concept that is still in its infancy. Therefore, in this paper, a visualisation of smarter meter data in a virtual reality setting, is demonstrated. The aim of the work is to i) outline an approach for data visualisation in virtual reality and ii) demonstrate how a virtual assistive environment can be created for remote healthcare monitoring.**

Keywords- Data Visualisation; Virtusal Reality, Smart Meter.

I. INTRODUCTION

Today, information generated from different domains continues to accumulate and is being collected at increasing rates as a consequence of living in a big data era [1]. This field is expected to keep growing and get more complex so it is important to innovate continually and develop new ways of understanding the gathered information [2]. The intricacy of the models used for analysis increase with the data complexity; this makes it even more of a challenge to deliver effective communication and visualisation of the data to end users. Therefore, in order to identify patterns and to provide insights about the data's architecture it is key to understand the information in a more convenient way. This should be achieved via the development of meaningful tools for the analyst and standard users.

The visual representation of data plays an important role when presenting complex findings in an informative and engaging way. This, combined with advanced analytics, can be integrated in methods to support the creation of interactive and animated graphics on different platforms, including desktops and various mobile computing devices [3]. However, less traditional visualisation methods, such as those using immersive Virtual Reality (VR) platforms, represent a powerful and innovative approach for multi-dimensional data visualisation that can outperform traditional desktop visualisation tools [4].

Smart meters are a rich source of granular electricity consumption data. This has raised considerable attention in the recent years on a global scale due to the numerous advantages smart meters provide [5]. Supported by the Advance Metering Infrastructure (AMI) [6], smart meters enable real-time monitoring of energy usage by recording electrical data such as voltage, frequency and energy consumption information [7]. This high-resolution data collected from smart meters can ultimately provide valuable information on the electricity consumption behaviours and lifestyle of the consumers. Therefore, allowing the development of remote monitoring systems to assess independent living in populations with Dementia or Alzheimer's disease [8]. In this sense, institutions such as the National Health Service (NHS) in the United Kingdom (UK) are able to use the data collected remotely to explore the data in a novel way and provide an assessment of the patient. Based on these ideas, a virtual assistive environment concept is simulated in this paper for remote healthcare monitoring using data collected from smart meters.

This paper focuses on the visualisation of smart meter data in a virtual reality setting to maximise the perception of the data scape geometry and provide a more intuitive way to explore high dimensionality and abstraction inherent in the data. The remainder of the paper is as follows. Section II presents a background discussion on visual data analytics in VR and highlights related projects. Section III outlines the methodology adopted for this work. Section IV presents the implementation and a discussion on the work. The paper is concluded in Section V.

II. BACKGROUND

VR interfaces have been broadly used in many fields including scientific visualisation with numerous commercial and academic software systems developed in the field of physics, astronomy, biology, medicine, and engineering among others [9]. The benefits of using such technology provides a better understanding and manipulation of the data which facilitates a more efficient and comprehensive analysis [10]. In this sense, VR technologies have the potential to assist decision makers when dealing with analytical tasks. Users can be immersed in the dataset to explore it from a different perspective, with the possibility of extracting knowledge from the inside-out instead of from the outside-in as typically conducted using 2D techniques.

 ISBN: 978-1-61208-724-5

A. Visual Data Analytics using Virtual Reality (VR)

Despite the success of VR in scientific visualisation, it is still in its infancy in the field of information visualisation. VR environments: immersive (specifically head mounted displays) and non-immersive (desktop) 3D worlds, where a virtual world is enhanced with abstract information.

Traditionally, Science Visualization [11] and Information Visualisation [12] have been the main areas of visualisations. In the first case, data from scientific experiments is represented using three-dimensional visualisations, with various uses in biology, medicine, architecture and meteorology among other fields. On the other hand, Information Visualisation emerged to facilitate the comprehension and interpretation of the data to users utilising graphics. In addition to these two areas of visualisation, the field of Visual Analytics [13] has emerged in the past few decades. Visual analytics (VA) combines visualisation, data mining and analysis methods with suitable user interaction. To provide advanced insights in the data, especially high dimensional data. Users can be immersed into the data via Immersive Analytics (IA), which is derived from the VR and VA fields, and uses stereoscopic visualisation to immerse an individual into a virtual environment.

VR has been used to model statistical visualisations in large sets of data points [14]. The authors in [14], for example, developed an application for statistical analysis using the C2 immersive VR environment [15], and then compared it against a more traditional workstation-based tool for high-dimensional data visualisation, XGobi [16]. Users were tested in how well they detected and selected clusters, intrinsic dimensionality and radial sparsity, using several graphic methods to analyse the data (i.e., brushing and grand tour). Results demonstrated that the added dimension provided by C2 enables the users to make better decisions about the structure of high dimensional data. This, in turn, indicates the benefits of using C2 environments to improve user's productivity for structure and feature detection tasks in comparison with XGobi. System experience plays an important role when analysing the data in favour of those users with more experience interacting with desktop environments. Slower interactions in the C2 system were apparent for people with no previous experience in VR. However, the intuitive nature of virtual environments can accelerate the learning process when using immersive environments such as C2.

The role of VR (and also Augmented Reality (AR) and Mixed Reality (MR)) in Big Data visualisation has been highlighted in [17]. The authors provide an overview of past and current visualisation methods in the field of Big Data while discussing important challenges and solutions towards the future of Big Data visualisation using immersive analytics (the combination of VR and Visual Analytics). These challenges are related to current technology development, as well as human limitations [18]. Advances using such techniques, will ultimately help improving human challenges related to their ability to manage the data, extract information and gain knowledge from it.

In the utility domain, VR has vaguely been explored with some exceptions where AR instead of VR has been used [19][20]. Therefore, this represents an ideal opportunity to investigate how Immersive Analytics can be used to extract knowledge from smart meter readings (i.e., anomalies). Angrisani et al. [19] utilised augmented reality to develop an approach to improve home power consumption awareness. The authors included sensors into the system, designated to measure power factor, current and active power consumed by household appliances. Experiments conducted using the AR reality system allowed users to access electrical consumption associated with appliances' corresponding load in a simple an easy way rendering the power values in a smart device (smartphone or tablet). Based on the information reported, the users were able to decide whether to switch the appliances off or not. The experiments conducted showed the potential of AR in energy monitoring within household context.

B. Virtual Reality Applications

Other VR applications have been explored in our previous work where we demonstrate the use of VR for training and productivity enhancement. For example, in [21], a VR crane simulation is outlined, as presented in Figure 1. The aim of the application is to train drivers/operators in a safe environment, improving the productivity behind the training stage of crane operation. The application allows the user to move the crane around and the view changes dynamically. The prototype shows where a crane can be positioned within a real-world 3D virtual environment, taking into account the swing and rotation of the crane beam.

Figure 1. Virtual Crane Simulation [13]

In [22], a VR proton beam therapy unit is constructed using an actual building information model of a proton beam therapy treatment unit. The application acts as a metric for supporting patients by providing an opportunity for the individual to be prepared mentally for the treatment process.

Figure 2. Virtual Proton Beam therapy Unit [14]

 ISBN: 978-1-61208-724-5

The application presented in Figure 2 has the potential to be a staff training metric. The interaction is simplified and provides an effective platform for inducting new staff into the treatment room and processes involved. Both projects are a clear demonstration of the role VR can play in the way we understand out environment, and it is a clear transformative technology for training and communication.

Building on this background investigation and our related VR development work, in the following section the methodology adopted for this project is presented.

III. Methodology

In the methodology, an overview of the process flow adopted for this research is presented. The data employed in the visualisation and the techniques used to structure the data for use in a VR setting are also outlined.

A. Process Flow

The process involves a six-step pipeline, as outlined in Figure 3.

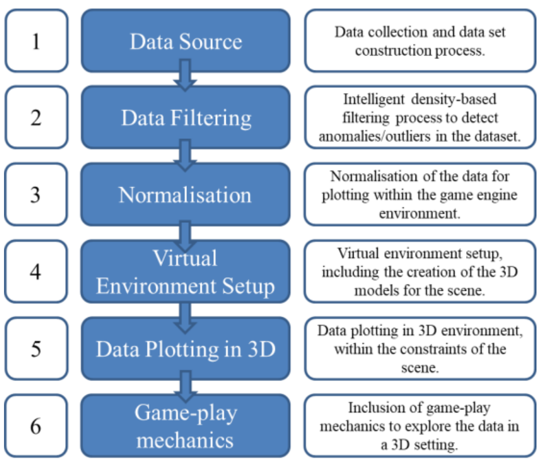

Figure 3. Process Flow

The data source in this paper is comprised of smart meter data from 10 homes, collected over twelve months. The energy readings are taken at 30-minute intervals. An overview of the data is presented in Figure 4, which displays the total energy usage for one individual in the dataset. The y-axis displays the KiloWatt Hour (KHW) energy usage and the x-axis is the rowID for the energy reading within the dataset.

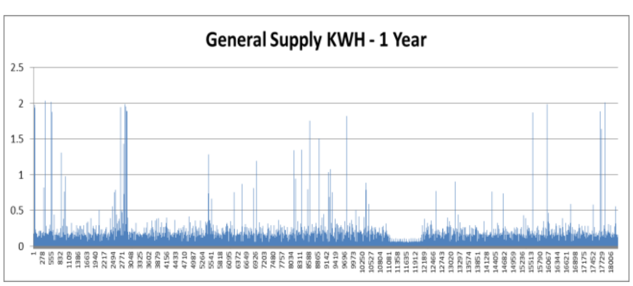

Figure 4. Data Overview

The x-axis, therefore, corresponds to time and displays the progression of the energy usage over one-year. However, it is the anomalous points in the data that are of specific interest. For example, patterns or changes in energy consumption, which deviate from the norm that may be indicated by an anomalous point in the dataset. Given the size of the dataset, simply visualising the raw data would not be an ideal metric for exploring the data in a virtual environment. For that reason, a Local Outlier Factor (LOF) algorithm is applied to the data.

B. LOF Clustering

The LOF process filters the data. Anomalies then stand out from the overall dataset. In order to calculate a LOF anomaly score, the number of variants according to the mathematical combination is calculated in (1). The LOF anomaly score measures the local deviation of density through determining how isolated the value given by k-nearest neighbours.

$$\binom{n}{k} = \frac{n(n-1)\dots(n-k+1)}{k(k-1)\dots 1} \tag{1}$$

A value of 1 indicates that an object is comparable to its neighbours (inlier). Likewise, a value below 1 indicates a dense region. A value significantly above 1 indicates an anomaly (outlier). Any value above 2 is considered, as we are interested in the higher-value outliers in the dataset to ensure that they are clear anomalies. The dataset, presented in Figure 4, is presented subsequently as a LOF plot in Figure 5. Through visualising the anomalies in this way, outliers can be highlighted more clearly, through deviations from the dense regions of data. Individual anomalous data points, with an associated time stamp, stand out by having a greater outlier value.

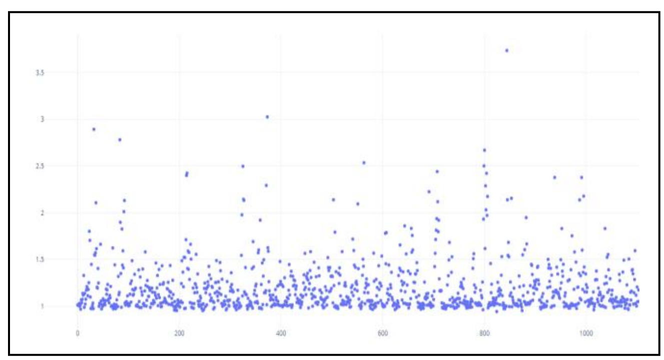

Figure 5. LOF Visualisation

Once the data had been processed through the LOF algorithm, it can be inserted into the VR environment.

IV. Implementation

For the 3D development, Unity game engine is employed. Models are created externally in a 3D modelling environment and imported into the scene.

 ISBN: 978-1-61208-724-5

A. Import Data into Unity

Inserting the raw LOF results into Unity process is displayed in Figure 6. The data points are represented by a simple smart meter 3D model in the 3D space. The LOF results are not constrained to a small space, and are disbursed of a significantly large area, which cannot be explored easily in a VR environment.

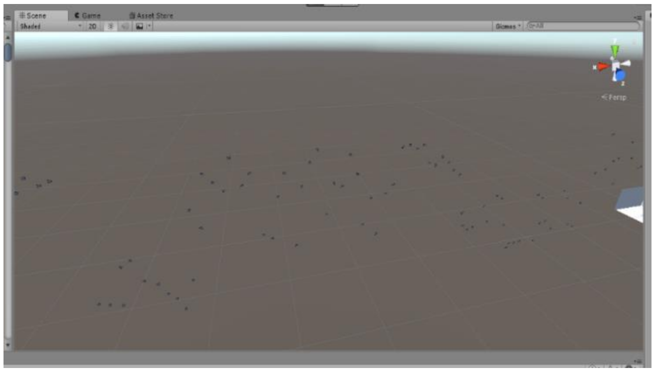

Figure 6[a]. Plotting Data in unity

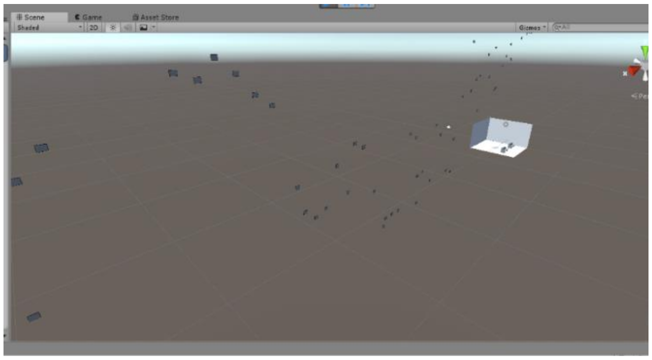

Figure 6[b]. Plotting Data in unity

The 3D data exploration room is visible in Figure 6b. This demonstrates the scale of the data plotted into the world. Ideally, the data should resemble a 3D plot of the LOF anomaly scores, such as the one displayed in Figure 7. Where, as before the x-axis shows the row ID from the dataset, the z-axis displays the anomaly score and the y-axis shows the density. In this case, the data is confined to a small 'explore-able' space.

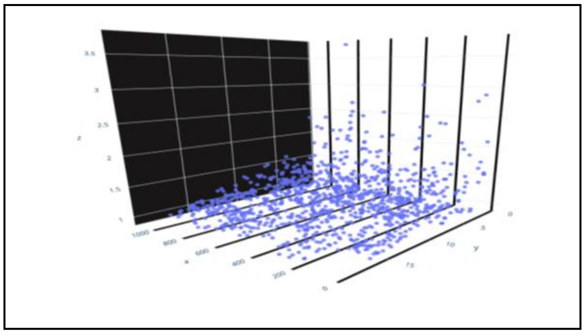

Figure 7. 3D LOF Plot

B. Normalising th Data on Import

Therefore, in order to constrain the data points to a room environment that would allow the user to explore the data requires a normalisation process. Within Unity, a 'data plot' game object is inserted, which correlates the data points to an x, y, z, co-ordinate in the 3D space. This is displayed in Figure 8. The process is achieved by scaling all the values between 0-1, with the maximum and minimum values from the dataset used to define the size of the data plot in the environment.

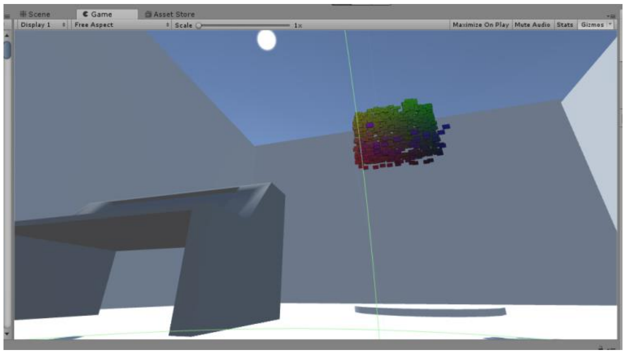

Figure 8. Data Normalisation

At this point, a First Person Shooter (FPS) asset is included in the game world, to allow the player to explore the environment and the dataset. The data plot is also moved closer to the floor, as displayed in Figure 9.

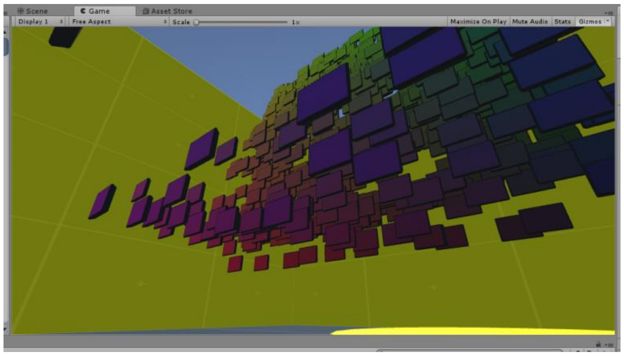

Figure 9. FPS View of the Data Plot

In an ideal setting, the game world would allow for multiple users, who can explore remotely and discuss the data patterns being visualised. To simulate this concept, characters are added, as displayed in Figures 10 and 11.

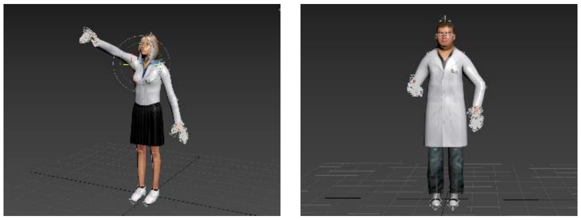

Figure 10. Scene Character Examples

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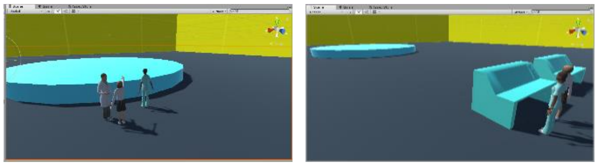

Figure 11[a]. Characters in Scene

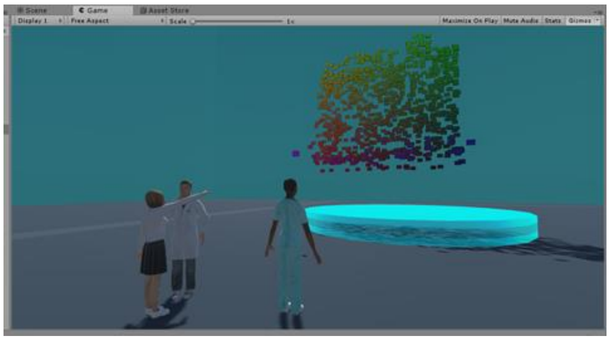

Figure 11[b]. Characters in Scene

The final prototype scene is displayed in Figure 11b. The centre disk is projected as a hologram within the scene. This is implemented using a shader in Unity. The interaction within the environment is rudamentary and can be presented using the standard KLM interaction times, as presented in Table II.

TABLE I. KLM INTERACTION TIMES

KLM Interaction Times - PC		
Task	Time (seconds)	Abbreviation
Mental preparation	1.35	M
Home on Keyboard/Mouse	0.40	H
Pointing	1.10	P
Press left click	0.10	Kl
Press right click	0.10	Kr
Turn left (A Key)	0.28	Kl
Turn right (D key)	0.28	Kr
Move Backward (W key)	0.28	Kb
Move Forward (S Key)	0.28	Kf

For example, walking around the room from the console to the data plot would inolve the following steps

$$Task\ A = M + H + \left(Sb * n\right) \tag{2}$$

C. Discussion

The next stage of the development is three-fold. 1) To set up the real-time insertion of data into the environment and 2) to integrate smart meter data at lower sampled intervals, as actual patient monitoring from 30-minute samples is a considerable challenge. For example, in related work, by using 10-second intervals the detection of household appliances is possible [7][8]. 3) At this stage we will employ supervised machine-learning algorithms, such as a Support Vector Machine (SVM) and the Bayes Point Machine binary classifier, to detect actual device interactions. Algorithms will be developed to construct device usage, time, day and device combinations. This forms the premise for actual activity construction within the home environment. This means the VR process could be personalise for individual use. In order to associate devices with behaviours, selected algorithms for behavioural modelling may include the back-propagation trained feed-forward neural network classifier, the levenberg-marquardt trained feed-forward neural net classifier, for example. These techniques are well-known algorithms and are selected for their ability to learn normal and abnormal values in a dataset [6-8]. By using the above techniques, the ambition of the work is to set up a real-time remote patient monitoring VR application.

V. CONCLUSION AND FUTURE WORK

This paper presents proof of concept demonstration of the use of VR and the integration of a dataset. The future direction of this work will include adding interactivity with the data point, so that users will be able to view the time stamp and the anomaly score of the data point. In addition, we will also experiment with the inclusion of other datasets so that the user will be able to view more than one person at once for the comparison purposes in the game environment. The NPC characters will be replaced by actual avatars of the users allowing clinicians to monitor patients remotely from a shared 3D environment.

ACKNOWLEDGEMENTS

This research project and the special track session are both funded by the EPRSC - EP/R020922/1. Owing to the ethical sensitive nature of this research, the data underlying this publication cannot be made openly available.

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