Visualizing Pipeline Sensors Datasets Using Augmented Reality Based Prototype

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Abstract

Pipeline sensors generates significant amount of multivariate datasets during normal and leak situations. Therefore we have developed a data model to effectively manage such data and enhance the computational support needed for the effective data explorations. In this paper we discuss the development of an Augmented Reality (AR) - based scientific visualization system prototype that supports identification, localisation, and 3D visualisation of oil pipeline leakages sensors datasets. A challenge of this approach is to reduce the data inefficiency powered by the disparate, repeated, inconsistent and missing attributes of most available sensors datasets. To handle this challenge, this paper aim to develop an AR-based scientific visualization interface which automatically identifies, localise and visualizes all necessary data relevant to a particularly selected region of interest (ROI) along the virtual pipeline. Necessary system architectural supports needed as well as the interface requirements for such visualizations are also discussed in this paper.

Keywords: Sensor Leakages Datasets, Augmented Reality, Sensor Data-Model, Scientific Visualization.

1. Introduction

Despite exponential increase in computing performance, the capabilities for visual analysis are still being challenged by the scale of data acquisition enabled by modern sensing and simulation technologies. Interactive data exploration and analysis relies heavily on visualisation tools to assist any user in discovering and interpreting hidden patterns within a large dataset. Scientists and engineers find it easy to identify patterns existing in long data streams by using visual cues such as shapes and colours Gross M. (1994). The vast amount of data generated by modern sensors tends to make most oil companies data-rich but information-poor. A computerized system that provides users with easy access to the sensors datasets captured at various instances on the pipeline can make identification and localisation of leakages more efficient. Such a system is intended to locate the necessary data and significantly reduce the time needed to spot 'danger zones' on the pipeline. There are many of such software systems that support localisation and identification of leakage points along the network popularly called the Leakages Detection Systems (LDSs), example of embedded technologies in LDSs includes the Volume or mass balance, the Rate of change in Flow or Pressure, the Hydraulic Modelling, the Pressure point analysis and the $ATMOS_{PIPE}$®

currently being used by Shell. Added to this, some private companies provide customised software solutions along with necessary hardware devices so that the oil companies can effectively monitor pipeline performance. Earlier methods employed for detection is by manual inspection which has been found human-intensive and cost ineffective. This paper presents an Augmented Reality (AR) approach that automatically detects leakages on the pipeline and superimposed the computer-generated data onto a visual display devise that can help the oil companies to reduce extra time used for identifying and locating leakages along a pipeline network of known dimension without a compromise of data reliability.

Researchers over years have tried to develop AR-based applications to support various types of datasets in several domains such as in architecture, engineering, and education. For example, Borgeat et al. (2005) developed a method for visualizing terabytes texture data from digital photographs and latter presented tools for analysing the data in the real time using the Atelier3D framework. This framework, principally used by many visualisation applications such as in movies was developed over many years, it became popular because many tools used to analyze 3D data are dispersed and mostly sometimes are inappropriate for the specific context of large datasets like the ones obtained from pipeline sensors. For most sensors' datasets, development of model is usually an accepted approach. These models usually have relatively simple structures, so, visibility culling of the data is rarely the main issue Borgeat et al., (2005). Model simplification by using quadric error metrics (Hoppe, 1999) was a popular approach, other methods such as that which renders hierarchies of points instead of meshes by Rusinkiewicz & Levoy (2000) and the meshes vertices order technique by Yoon et al. (2005) were also developed, although this has been found disadvantageous when the rendering quality is of utmost significance (Zwicker et al., 2004). The main challenge in large data visualization therefore is to be able to adapt in real-time the resolution of the rendered data to the resolution of the display Borgeat et al. (2005). Visualization techniques generally are focused on reducing the voluminous data into manageable 'data figments' displayable by common display devises and allows extensive exploration without a compromise of image resolution and or quality when it is desired.

Visualisation of large datasets especially the ones that has a link with information browsing was developed by Reitmayr & Schmalsteig (2004). However, because their model could only be used with static datasets, it is inapplicable for sensors' applications. In a position paper on sensor data visualization on outdoor augmented reality, Sean White (2009) presented the visualisation of Carbon monoxide (CO) sensor data as an example of visualisation approach that supports dynamic sensor data with inputs from a 'data importer' using the SiteLens system earlier proposed by them. The method they employed involves the use of mobile sensors which can be used for displaying datasets as they are sensed on the scene in real time. Problems such as information overload, detecting the presence of hidden information and filtering visualizations are often the aftermaths of such visualisation method. Some researchers such as Julier et al. (2000) and Sean White (2009) had attempted solutions to the problem although Sean's approach was more of data selection and filtering. The benefits of this is real time interactivity and this is something the industries making use of pipeline to transport materials really need. In architecture, the PDA-based Augmented Reality Integrating Speech (PARIS) that allows interactivity with the system by voice was developed by Goose et al. in 2004.

2. AR for Sensors' Datasets Visualization

Sensors datasets are prone to errors for so many reasons which are either classified as systematic or random errors Eiman & Badri (2003). Building AR visualisation system for

pipelines sensors datasets require that a number of processes must be strictly followed. The sensors must be properly calibrated Bychkovskiy et al. (2003), the generated datasets must be screened for noises, inaccuracies, imprecision, emptiness and redundancies because sensors are not consistent in their measurement of the same phenomenon under the same conditions. Further, the 'clean' datasets must undergo dimensionality reduction Keim & Kriegel (1995), and the reduced datasets must be rendered using appropriate tools. ARToolkit® has been a popular tool for such visualisations.

Many manufacturers and designers of sensors have developed techniques for cleaning and correction of error for wireless sensor datasets examples are found in Elnahrawy et al. (2003) and Fishkin, et al. (2004). Some systems uses models of sensor datasets to accurately and efficiently answer wireless sensor network queries with defined confidence intervals Deshpande, et al. (2004). For example, TinyDB provides a declarative means of acquiring data from a sensor network. Application Level Events (ALE) defines an interface for building middleware for some applications; ALE defines concepts similar to what is described as temporal and spatial data granules. The Context Toolkit (CT) advocates an architectural approach to hiding the details of sensor devices Dey (2000) .Visual data mining VDM incorporates the users in data extraction process Keim (2002). There is also the regression method which was applied to sensor networks for inference purposes by Paskin et al. (2005) which was basically an approach that involves building and maintaining complex models.

Current hardware technologies have developed means of storing these vast amounts of sensors' datasets. Even if all the entire display pixels are used for displaying the datasets, only a limited fraction of this could be rendered which greatly limits the capacity for intensive visual exploration of the entire database. Hidden data patterns are a problem both to the data user and visualisation experts. Towards the wake of this last decade, emphasis on data exploration became a research problem, people now seek patterns in datasets more intuitively and wish to have certain level of interactions. Scholars have proposed techniques for representing datasets and interacting with them, Ware C. and Beatty, J. C. (1988), MacAdam D.L. (1942, 1971). Immersive Virtual Reality (IVR) emerged as a way forward that gives any user the ability to interactively explore and understand complex phenomena by mapping the numeric datasets into virtual shapes, providing means to interact with these data-shapes by manipulating their orientations and gaining insight into the hidden structures within the datasets during analysis Dam A.S. et al. (2000). The limitation of the IVR technology is that it requires arbitrary vectors in the datasets before the transformation into the 3D glyphs Sangole A. et al. (2003). If the exploration of very large datasets must be successful therefore, it is necessary to integrate humans as part of the data analysis process. It will be important to combine the best features of humans and computers Keim & Kriegel (1995). Hence, the AR-based visualisation approach proposed in this paper seems to be a way forward.

3. Proposed Data Model

During a typical flow in pipelines the sensors captures a vast amount of data that represents the instantaneous situation of the flowing material. Naturally, computerised systems such as the Leakage Detection Systems (LDSs) can help to visualise the flowing material but not with the associated data attributes. The data attributes and their respective orders are very important for such visualizations. Generally, some data points in real life have no inherent order while for others, order is a significant issue. All vectors of the pipeline sensors' datasets are ordered and aggregated, meaning that they all are ordinals. Sometime they are continuous and most of the time intimately intra connected with missing and erroneous data points (see example in Table 1) or what we described in this paper as outliers.

Table 1. Typical Reading Extracted from a Sensor-Velocity Volume Vane Thermo-Anemometer[1] Manufactured by KOREC DIRECT®

Time (milli.sec.)	Pressure (N/m[2])	Temp. ([0]C)	Vol. (M[3]/H) x E-03	Flow Velocity (m/s)	External body force (N)	Classification
00:00:00	-	-	-	-	-	Nil
00:00:01	1.002312	19.302978	0.0055546	12.002302	-	Normal
00:00:02	1.002202	19.302990	0.0055544	12.002302	0.000344	Normal
00:00:03	-	19.302990	-	-	0.002765	Turbulence
00:00:04	0.903421	-	-	12.003421	-	Turbulence
00:00:05	1.002212	19.302978	0.0055546	12.004523	-	Normal
00:00:06	-	18.999996	0.0055544	12.005620	0.003452	Leakage
00:00:07	0.960620	18.999996	-	-	-	Leakage
00:00:08	1.002801	-	-	12.002302	0.003564	Steady
00:00:09	1.002376	19.302978	-	12.002302	0.005423	Turbulence
00:00:10	-	18.999996	-	-	0.005642	Leakage
.	.	.	.	.	.	
.	.	.	.	.	.	

The questions are: what combination of these datasets attributes represents what situation on the pipeline?   And which data attribute could be used as test attribute for such classification without compromising data integrity? To answer these questions we resulted into data classification method using the decision tree algorithm proposed by Han & Kamber (2001). The data above is classified into 5 different possible states on the pipeline which are: Steady, Leakage, Turbulence, Normal and the Nil or (unclassified state). Further, we set boundaries[2] for each state with respect to each attributes as shown in Table 2.

Table 2. Showing Typical Attributes Boundaries

	Pressure (p)	Temperature (t)	Volume (v)	Flow Vel. (f)	Ext. Force (e)
	$p \leq 0.97$	$t \leq 12.1$	$v \leq 0.0054$	$f < 12.0$	$e < 0.003$
	$0.98 \leq p \leq 1.3$	$12.2 \leq t \leq 20.0$	$v \geq 0.0055$	$f \geq 12.0$	$0.003 \leq t \leq 0.005$
Boundaries	$p \geq 1.4$	$t \geq 21$	-	-	$e \geq 0.006$

As shown in Figure 1, the proposed data model supports five activities that occur in different phases during a typical visualization of sensor's flow datasets. The five activities are Data capture, Data cleaning and classifications, Dimensionality reduction, Data aggregation, and Data visualization. Data captured from various sensors positioned at different locations along the pipeline network are injected into the system directly. Data cleaning and classification begins by pruning the data of emptiness, repeated values and generating a decision tree for the data using the basic algorithm for inducing a decision tree by Han & Kamber (2001 p.285). To address the issues of uncertainties in the captured datasets in the

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[1] Source- NNPC, Nigeria

[2] Courtesy Annual report 2005-2006 of the Nigerian National Petroleum Corporation (NNPC)

developed interface, we have employed the Uncertainty Treatment Algorithm (UTa-algorithm) that we developed earlier Folorunso et al. (2009). Human involvement is noted as part of the third to fifth activities to reducing the data dimension, aggregating and visualising the ROI particular to a user.

Let S be a set of sensor data samples captured at different locations on the pipeline and si be the number of sample S in class Ci, if there are Ci distinct classes into which the data could be classified, then to compute the information gain by each sensor data, we first compute the expected information needed to classify the given data. The information needed is defined by:

$$I(s_1, s_2, \ldots s_m) = -\sum_{i=1}^{m} p_i \log_2(p_i)$$

Where pi = si/s is the probability that an arbitrary sensor data belong to a class Ci . Log base 2 has been used because the data are encoded in bits. Using Table 1, (m=5) since there are five possible distinct classes/states. Let C1= Steady, C2= Leakage, C3= Turbulence, C4= Normal and C5= Nil states. Then from Table 1, it implies that C1= 1, C2= 3, C3= 3, C4= 3 and C5= 1.

Therefore

$$I(s_1, \ldots, s_5) = -\frac{1}{11}\log_2\frac{1}{11} - \frac{3}{11}\log_2\frac{3}{11} - \frac{3}{11}\log_2\frac{3}{11} - \frac{3}{11}\log_2\frac{3}{11} - \frac{1}{11}\log_2\frac{1}{11}$$

$$I(s_1, \ldots, s_5) = 2.163$$

The next thing is to compute the entropy of each sensor data attribute. Beginning with pressure and continuing with other attributes such as temperature, volume, flow velocity and the external body force. (Note that time has been ignored. Its impact will be discussed latter).

When pressure = "$p \leq 0.97$",

$$s_{11}=0, s_{21}=1, s_{31}=1, s_{41}=0 \text{ and } s_{51}=0$$

Therefore using equation 1,
$$I(s_{11}, s_{21}, s_{51}) = 1.000$$

When pressure = "$0.98 \leq p \leq 1.3$",

$$s_{12}=1, s_{22}=0, s_{32}=1, s_{42}=3 \text{ and } s_{52}=0$$

Similarly, $I(s_{12}, s_{22}, s_{52}) = 1.371$

When pressure = "$p \geq 1.4$",
$$s_{13}=0, s_{23}=0, s_{33}=0, s_{43}=0 \text{ and } s_{53}=0.$$

Similarly, $I(s_{13}, s_{23}, s_{53}) = 0.000$

Therefore, if the captured sensors data is partitioned based on the pressure attribute, the expected information needed E(p) could be computed using:

$$E(p) = \sum_{j=1}^{k} \frac{s_{1j} + \cdots + s_{mj}}{s} I\left(s_{1j} \ldots s_{mj}\right)$$

With k=3 (the number of possible boundaries for data attribute pressure) and m=5 (the number of attributes). Therefore,

$$E(p) = \frac{2}{7} I(s_{11}, s_{21}, \ldots s_{51}) + \frac{5}{7} I(s_{11}, s_{21}, \ldots s_{51}) + \frac{0}{7} I(s_{11}, s_{21}, \ldots s_{51}) = 1.265$$

Finally, the Gain in information from partitioning using pressure attribute is computed using:

$$Gain\ (pressure) = I(s_1, .., s_5) - E(p)$$

or

$$Gain\ (pressure) = \mathbf{0.898}$$

The Gains computed for other attributes are presented in Table 3.

Table 3. Showing Computed Gains for All the Listed Attributes

Data Attribute	Gain
Pressure (p)	0.898
temperature (t)	0.673
volume (v)	**0.944**
flow velocity (f)	0.445
external body force(e)	0.429

Data Attribute volume (v) with the greatest Gain (0.944) is then chosen as the test attribute for classifying the sensors data. This approach for data classification is tainted with problems of noises and outliers. Often, statistical means is often an approach to dealing with these problems Han & Kamber (2001). In the programming logic of the developed AR-based interface described in this paper, a slightly different approach - the Minimum Description Length (MDL) principle Han & Kamber (2001) is adopted to prune the attributes simply because of its insensitivity to the sampled sensor datasets.
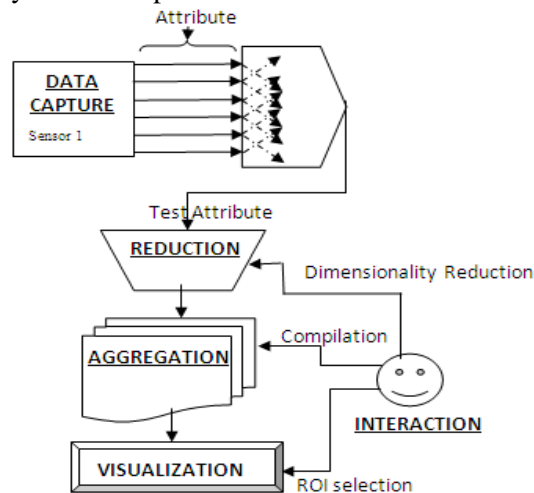

Figure 1. AR-Based Data Model for Sensor Datasets

4. The AR-Based Visualization Interface

Using AR in visualisation is still in the development phase and such visualization solutions generally depend on design decisions. There are three things that must be in mind when designing an AR application for visualization; Combination of both the real and the virtual data, Real time data Interactivity and Registration in 3D Azuma (1997). One of the challenges in our modelling was to reduce inefficiency caused by the following factors: noises from external sources, sensors' measurement inaccuracies, random errors generated by the hardware, and computing imprecision that is included in the model. These exceptions or outliers are generally ignored during visualisation but their effects could become very significant if appropriate measures are not taken. One way forward to meeting this challenge is to develop an AR-based data visualization interface which can automatically detect selected location along the pipeline and visualize only the necessary datasets relevant to the particular location. In this section, we discuss the interface requirements and the architecture that is required for such interface.

4.1. Interface Requirement 1

The visualization interface shall model the pipeline system in a way that users can specify the overall length[3] of the pipeline. Visualization of the pipeline sensors' datasets requires that the whole length of the pipeline should be known and that the pipeline in question should be displayed and calibrated. In our model, a user specifies the length of the pipeline to be model and the interface automatically displays and calibrates the pipeline in kilometres (km) as shown in Figure 2 a & b.
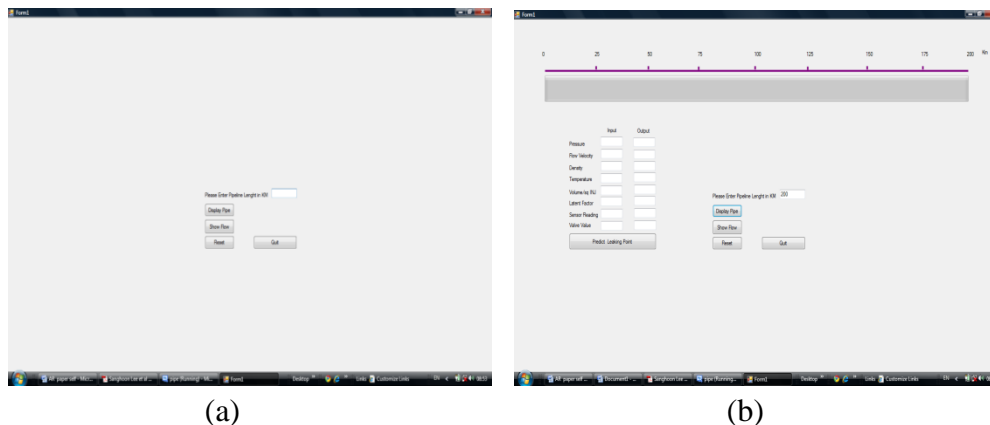

(a)   (b)

Figure 2. Interfaces Snapshots for Capturing (a) and Displaying (b) the Pipeline Length

4.2. Interface Requirement 2

The interface shall select and visualize only the necessary attributes-region of Interest (ROI) of the captured sensors' datasets. Various types of sensors generate different kinds of attributes. No single sensor device could generate all the required attributes, the user through

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[3] An assumption here is that the pipeline has no bends or Ts although this is the situation in real life pipeline networks

the interface selects the attributes particular to the governing sensor device. We have designed the interface as shown in Figure 2(b) to select only the required attribute for the visualisation. For a typical visualization, not all the attributes are needed the test attribute is simply determined by procedure "find_test_attribute" embedded in the program logic making use of the basic algorithm for inducing a decision tree by Han & Kamber (2001) discussed earlier in this paper.

4.3 Interface Requirement 3

The interface shall be built in such a way that it will allow users' selection into of the ROI and interaction with the last three activities of the data model. In order to know the precise state of the pipeline at a specified region, all the captured and processed data for the region must be rendered. To achieve this, the interface shall be structured to provide interactivity with the data reduction, data aggregation and the data visualization stages of the model. This will ensure that only the ROI is displayed and the rest data are 'hid' from the scene.

4.4 Interface Requirement 4

The interface shall be made in such a way that it could detect and report the exact leakage location on the pipeline. Leakages localisation is principal to the heart of this kind of visualization, the interface shall be built to use the selected ROI sensor datasets to effectively predict and localize the leakage point on the pipeline based on the available datasets. Automatic identification and localisation of the leakage point on the pipeline network can easily facilitate the process of correcting the pipeline anomaly as well as guiding the user throughout the data exploratory process. Currently the methods available for such localization essentially make use of the results from the LDSs which are often corrected offline. The time lag between the data capture and the localisation times in these systems could become significant for time sensitive cases of localisation. Examples of problems arising from such delayed localisation are those of the Ejigbo pipeline explosion in Nigeria that claimed thousands of life and the August 19, 2000 event of a Natural gas pipeline rupture and fire near Carlsbad, New Mexico. This explosion killed 12 members of the same family.

5. Results and Discussion

Input from the sensors are normalised into a native Microsoft Excel format with each attribute represented by the columns and the instantaneous data captures as the rows. Because of the (maximum rows) limitation of Excel, the captured data are automatically and periodically handled by a data screening module before a data-spill occurs. The native limit set in the interface was 20,000 data inputs. The retrieved data are then processed and visualised by proper modules, building the necessary pipeline models and superimposing in 3D AR space of the OpenGL-based rendering engine so that users can intuitively interact and with the entire network.

A separate module 'leakage_detection_R1' is designed to report leakage datasets if one is encountered. Figures 3 a & b shows an illustration with pipeline length 290km. After the rendering of the calibrated pipeline and data captured through appropriate modules, the interface reports that a leak is reported at kilometre 218.06 ($\pm$1.05) from the pipe origin as shown in Figure 4. Manual analysis of the data produced the error at kilometre 220km. The margin of the error is generally considered insignificant because repeated trials yielded results within the data boundaries (216.85, 221.23). To clear any doubts, we have also incorporated a

separate module 'leakage_predictor_R1' activated by a button "Predict Leakage" on the interface to predict the leakage points based on the 'means of nearby points' commonly used by most statistical packages including the SPSS v 16 for predictions. The 'leakage_predictor_R1' returns values within the range 217.20 to 219.30 which falls within the acceptable data boundaries for the specific set of data.
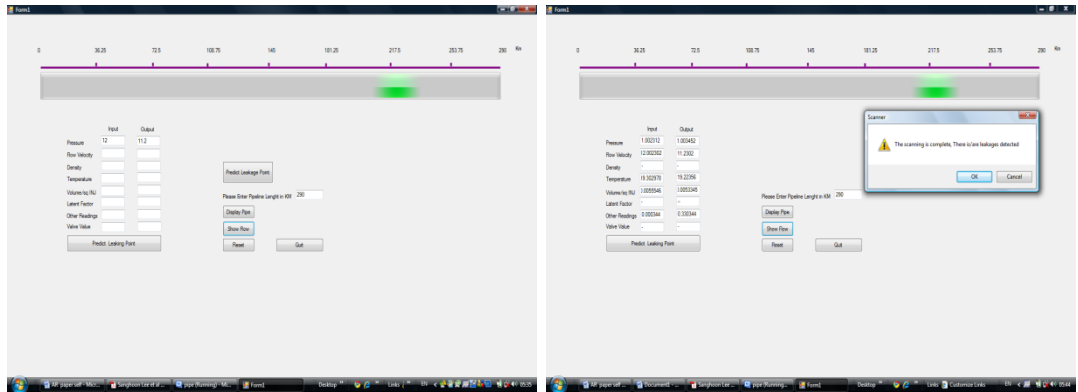
(a)   (b)

Figure 3 Interfaces Snapshots for Reading the Captured Datasets from the Excel Worksheets (a) and Displaying the Localised Leakage Point (b) on the Pipeline Network
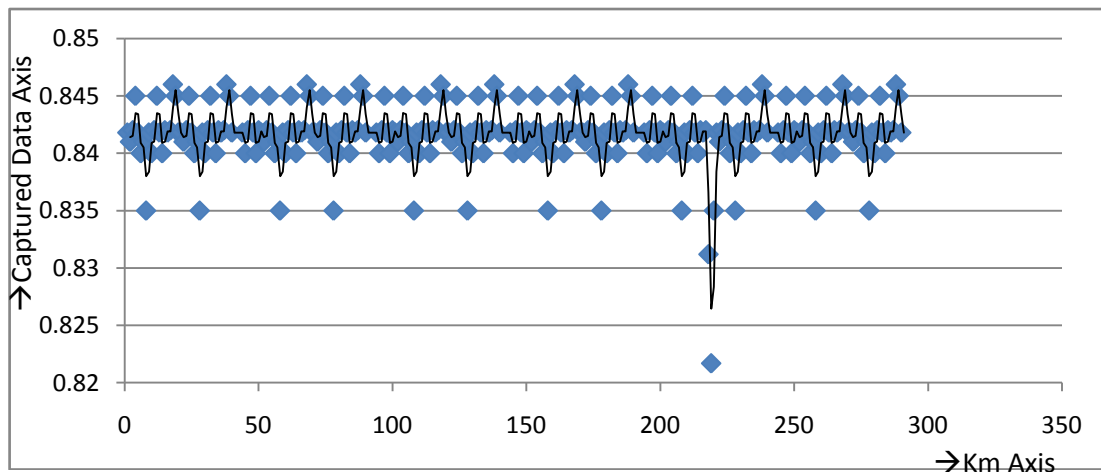

Figure 4. Graph Showing Reported Leakage at Kilometre 218.06 (±1.05)

6. Conclusions

We have presented in this paper the development of an AR-based scientific visualization interface that automatically identifies, localises and visualizes all necessary data relevant to a particularly selected region of interest along the pipeline. The necessary interface requirements to support efficient data capture, rendering and visualization are also discussed. An AR-based data visualization interface can improve localisation of leakage points along the pipeline network as well as reducing the operational costs associated with 'pigging'. Using

this AR-based approach improves access time to data without a compromise of data reliability. We have designed the interface to retrieve data stored only in 2D data formats using the native Microsoft Excel worksheets.

7. Future Works

Application and incorporation of 3D data input formats and extension of this work to handling atmospheric and geo-data are the future directions of this work.

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