

# A Prototype of Augmented Reality for Visualising Large Sensors' Datasets

Folorunso Olufemi Ayinde, Mohd Shahrizal Sunar, Sarudin Kari and Dzulkifli Mohamad

**Abstract**—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 leakages sensors datasets. 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. 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 network. Necessary system architectural supports needed as well as the interface requirements for such visualizations are also discussed in this paper.

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

## I. INTRODUCTION

**I**NTERACTIVE 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 [14]. 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. The vast amount of data generated by modern sensors tends to make most oil companies data-rich but information-poor. A computerised system that provides users with easy access to the sensors datasets captured at various instances on the pipeline network 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 network. 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<sub>PIPE</sub> 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 network 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 network and superimposed the computer-generated data onto a visual display device that can help the oil companies to reduce extra time used for identifying and locating leakages along a 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, [5] 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 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 [5]. Model simplification by using quadric error metrics [16] was a popular approach; other methods such as that which renders hierarchies of points instead of meshes by [18] and the meshes vertices order technique by [26] were also developed, although this has been found disadvantageous when the rendering quality is of utmost significance [27]. 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 [5].

Visualization techniques generally are focused on reducing the voluminous data into manageable 'data figments' displayable by common display devices 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 [12]. 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, [25] presented the visualisation of Carbon monoxide (CO) sensor data as an example of

Folorunso Olufemi A. is a researcher in Visualisation at the Universiti Teknologi malaysia; (e-mail: femi\_folorunso@yahoo.com).

Mohd Saharizal Sunar is a senior lecturer in computer graphics at the Universiti Teknologi malaysia; (e-mail: shah@fsksm.utm.my).

Sarudin Kari is an associate professor in Visualisation at the Universiti Teknologi malaysia; (e-mail: sarudin@utm.my).

Dzulkifli Mohamad is a professor of image and patterns recognition at the Universiti Teknologi malaysia; (e-mail: dzulkifli@utm.my).

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 [23] and [24] had attempted solutions to the problem although the latter'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 [13].

## II. AR FOR SENSORS' DATASETS VISUALIZATION

Sensors datasets are prone to errors for so many reasons which are either classified as systematic or random errors [10]. Building AR visualisation system for sensors datasets require that a number of processes must be strictly followed. The sensors must be properly calibrated [6], 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 [7], 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 [10] and [17]. Some systems uses models of sensor datasets to accurately and efficiently answer wireless sensor network queries with defined confidence intervals [1]. 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 [2]. Visual data mining VDM incorporates the users in data extraction process [8]. There is also the regression method which was applied to sensor networks for inference purposes by [21] 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, [4], [19,20] 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 [9]. The limitation of the IVR technology is that it requires arbitrary vectors in the datasets before the transformation into the 3D glyphs [3]. 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 [7]. Hence, the AR-based visualisation approach proposed in this paper seems to be a way forward.

## III. 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 a typical pipeline sensor' 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.

The questions are: what combination of these datasets attributes represents what situation on the network? 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 [15]. The data above is classified into 5 different possible states on the pipeline network which are: Steady, Leakage, Turbulence, Normal and the Nil or (unclassified state). Further, we set boundaries for each state with respect to each attributes as shown in Table 2.

TABLE I  
SHOWING TYPICAL READING EXTRACTED FROM A SENSOR-VELOCITY  
VOLUME VANE THERMO ANEMOMETER<sup>1</sup> MANUFACTURED BY KOREC  
DIRECT®

Time (milli.sec.)	Pressure (N/m <sup>2</sup> )	Temp. (°C)	Vol. (M <sup>3</sup> /H) x E-03	Flow (m/s)	Velocity	External force (N)	body	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
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.

TABLE II  
SHOWING TYPICAL ATTRIBUTES BOUNDARIES

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

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 [15, p.285 ] To address the issues of uncertainties in the captured datasets in the developed interface, we have employed the Uncertainty Treatment

Algorithm (UTa-algorithm) that we developed earlier [11]. 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 network 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:

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

Where  $p_i = s_i/s$  is the probability that an arbitrary sensor

<sup>1</sup> Source NNPC Nigeria

data belong to a class  $C_i$ . Log base 2 has been used because the data are encoded in bits.

Using the 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

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

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

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 = “ $p \leq 0.97$ ”,  
 $s_{11}=0$ ,  $s_{21}=1$ ,  $s_{31}=1$ ,  $s_{41}=0$  and  $s_{51}=0$ .

Therefore using eq.1,  
 $I(s_{11}, s_{21}, \dots, s_{51}) = 1.000$

When pressure = “ $0.98 \leq p \leq 1.3$ ”,  
 $s_{12}=1$ ,  $s_{22}=0$ ,  $s_{32}=1$ ,  $s_{42}=3$  and  $s_{52}=0$ . Similarly,  
 $I(s_{12}, s_{22}, \dots, s_{52}) = 1.371$

When pressure = “ $p \geq 1.4$ ”,  
 $s_{13}=0$ ,  $s_{23}=0$ ,  $s_{33}=0$ ,  $s_{43}=0$  and  $s_{53}=0$ . Similarly,  
 $I(s_{13}, s_{23}, \dots, s_{53}) = 0.000$

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

$$E(p) = \sum_{j=1}^k \frac{s_{1j} + \dots + s_{mj}}{s} I(s_{1j} \dots s_{mj}) \quad (2)$$

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

$$E(p) = \frac{2}{7} I(s_{11}, s_{21}, \dots, s_{51}) + \frac{5}{7} I(s_{12}, s_{22}, \dots, s_{52}) + \frac{0}{7} I(s_{13}, s_{23}, \dots, s_{53}) = 1.265$$

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

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

or

$$Gain(pressure) = 0.898$$

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

TABLE III  
 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 [15]. In the programming logic of the developed AR-based interface described in this paper, a slightly different approach - the Minimum Description Length (MDL) principle in [15] is adopted to prune the attributes simply because of its insensitivity to the sampled sensor datasets.

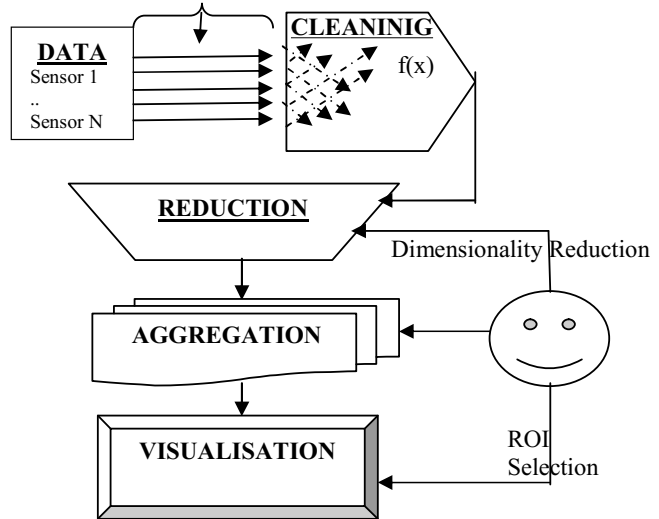


Fig. 1 AR-Based data model for sensor datasets

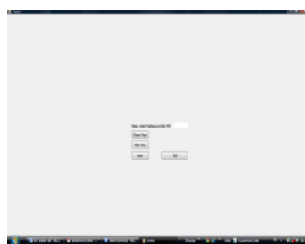
IV. THE AR-BASED VISUALIZATION INTERFACE

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

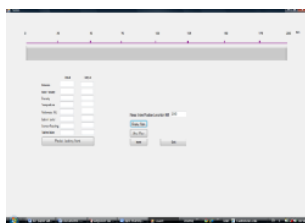
designing an AR application for visualization; Combination of both the real and the virtual data, Real time data Interactivity and Registration in 3D [22]. One of the challenges in our modelling was to reduce inefficiency caused by the following factors: noises from external sources, sensors' measurement 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 network 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.

#### A. Interface Requirement 1

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



(a)



(b)

Fig. 2 Interfaces snapshots for capturing (a) and displaying (b) the pipeline length

#### B. 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 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

<sup>2</sup> An assumption here is that the pipeline has no bends or Ts although this is the situation in real life pipeline networks

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 [15] discussed earlier in this paper.

#### C. 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 network 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.

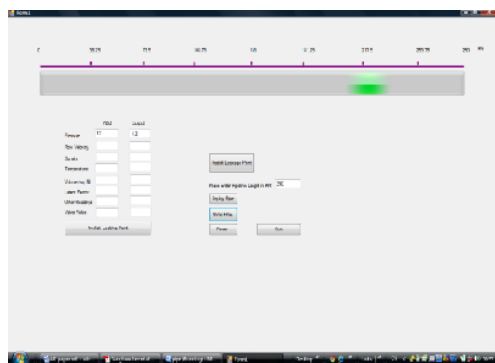
#### D. Interface Requirement 4

The interface shall be made in such a way that it could detect and report the exact leakage location on the network. 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 network 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.

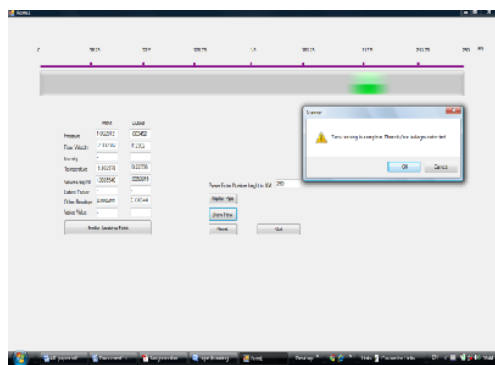
Input from the sensors are normalised into a native Microsoft Excel format with each attribute represented by the columns and the instantaneous data captures as the rows. Because of the (maximum rows) limitation of Excel, the captured data are automatically and periodically handled by a data screening 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 visualized by proper modules, building the necessary pipeline network 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. 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)

Fig. 3 Interfaces snapshots for reading the captured datasets from the excel worksheets (a) and displaying the localised leakage point (b) on the pipeline network.

## V. 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 entire network. 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.

## VI. FUTURE WORK

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.

## VII. ACKNOWLEDGEMENTS

This work is jointly supported by the UTMVicubeLab, FSKSM, Universiti Teknologi Malaysia and the Yaba College of Technology, Yaba, Lagos, Nigeria. We thank the Nigerian National Petroleum Corporation (NNPC) for the release of necessary data to test run the application at various stages. Special thanks to MOHE and Research Management Centre (RMC), Vot.77325 grant for providing financial support of this research

## REFERENCES

- [1] A. Deshpande, C. Guestrin, S. Madden, J. Hellerstein, and W. Hong. Model-Driven Data Acquisition in Sensor Networks. Proceedings of Conference on Very Large Data Bases (VLDB) Conference, August, 2004.
- [2] A. K. Dey. Providing Architectural Support for Building Context-Aware Applications. Ph.D. thesis, Georgia Institute of Technology, 2000.
- [3] Archana Sangole and George K. Knopf. Visualisation of randomly ordered numeric data sets using spherical self-organising feature maps. Elsevier Journal of Computer and Graphics. Vol. 27, 6, 2003, pp. 963-976.
- [4] Beatty, J. C. & Ware C. Using colour dimensions to display data dimensions, Human Factors. Vol. 30, 2, 1988, pp. 127-142.
- [5] Borgeat Louis, Guy Godin, Francois Blais, J-Angelo Beraldin, Philippe Massicotte and Guillaume Poirier, Visualizing and analyzing large and detailed 3d datasets. Visual Information Technology Group, Institute for Information Technology, National Research Council of Canada, Ottawa, Ontario, Canada, 2005, pp.1-9.
- [6] Bychkovskiy, V., Megerian, S., Estrin, D., & Potkonjak, M.A. Collaborative approach to in-place sensor calibration. Proceedings of the International Conference on Information Processing in Sensor Networks (IPSN)'03, (2003).
- [7] D. A. Keim, H.P. Kriegel. Issues in Visualizing Large Databases. Proceedings of the International Conference on Visual Database Systems (VDB-3). Lausanne, Schweiz, März, in: Visual Database Systems, Chapman & Hall Ltd., 1995.
- [8] D. A. Keim. Information visualisation and visual data mining. IEEE Transaction on Visualisation and Computer Graphics. Vol. 7,1, 2002, pp. 100-7
- [9] Dam, A.S. Forsberg, D.H. Laidlaw, La Viola J.J., Jr & Simpson R.M. Immersive VR for scientific visualization-a progress report. IEEE Computer Graphics and Applications. Vol. 20, 6, 2000, pp. 26- 52.
- [10] E. Elnahrawy and Badri Nath. Cleaning and querying noisy sensors. Proceedings of the 2nd ACM international conference on Wireless sensor networks and applications WSNA '03, 2003.
- [11] Folorunso Olufemi A., Mohd Shahrizal & Sarudin Kari. An algorithm for treating uncertainties in the visualization of pipeline sensors datasets. Proceedings of the First Int'l Visual Informatics Conf. IVIC '09, Kuala Lumpur, Malaysia, 2009. pp. 561-572.
- [12] G. Reitmayr and D. Schmalstieg. Collaborative Augmented Reality for Outdoor Navigation and Information Browsing. Proceedings of Symp. Location Based Services and TeleCartography, pp. 31-41, 2004.
- [13] Goose S., Güven S., Zhang S., Sudarsky S. and Navab N. PARIS: Fusing Vision-based Location Tracking with Standards-based 3D Visualization and Speech Interaction on a PDA. Proceedings of IEEE DMS 2004 International Conference on Distributed Multimedia Systems, San Francisco, CA, pp. 75-80.
- [14] Gross M. Visual computing, the integration of computer graphics. Visual Perception and Imaging. Springer, Berlin, 1994.
- [15] Han Jiawei & Micheline Kamber. Data Mining: concepts and techniques. Morgan Kaufmann Publishers, 2001.
- [16] Hoppe, H. New quadric metric for simplifying meshes with appearance attributes. Proceedings IEEE Visualization 1999. IEEE Computer Society Press, pp. 59-66.

- [17] Kenneth P. Fishkin, Bing Jiang, Matthai Philipose, Sumit Roy. I Sense a Disturbance in the Force: Unobtrusive Detection of Interactions with RFID-tagged Objects. In UbiComp, IRS-TR-04-013 Intel Research Seattle tech memorandum. June, 2004. pp. 1-17
- [18] Levoy, M., Pulli, K., Curless, B., Rusinkiewicz, S., Koller, D., Pereira, L. et al. The Digital Michelangelo Project: 3D scanning of large statues, Proceedings of ACM SIGGRAPH, Computer Graphics Proceedings, Annual Conference Series, ACM, 2000, pp. 131–144.
- [19] MacAdam D.L. Geodesic chromaticity diagram based on variance of colour matching by 14 normal observers. Applied Optics Journal. Vol. 10, 4, 1971, pp. 1-7.
- [20] MacAdam D.L. Visual sensitivities to colour differences in daylight. Journal of the Optical Society of America. Vol. 32, 5, 1942, pp. 247-274.
- [21] Mark A. Paskin, Carlos Guestrin and Jim McFadden. A robust architecture for distributed inference in sensor networks. In IPSN, 2005. pp.1-8.
- [22] Ronald T. Azuma. A Survey of Augmented Reality. In Presence: Teleoperators and Virtual Environments. Vol 6, 4 (August 1997), 355-385.
- [23] S. Julier, M. Lanzagorta, Y. Baillot, L. Rosenblum, S. Feiner, T. Höllerer, and S. Sestito. Information filtering for mobile augmented reality. Proceeding of the ACM and IEEE ISAR, 2000, pp. 3-11.
- [24] Sean White and S. Feiner. SiteLens: situated visualization techniques for urban site visits. Proceedings of the ACM CHI, Boston, MA, USA, 2009, pp. 1117-1120.
- [25] Sean White. Interaction with the Environment: Sensor Data Visualization in Outdoor Augmented Reality-a position paper, 2009.
- [26] Yoon, S.-E., Lindstrom, P., Pascucci, V. and Manocha, D. Cache-oblivious mesh layouts. ACM Trans. Graph, Vol. 24(3), 2005, pp. 886–893.
- [27] Zwicker, M., Räsänen, J., Botsch, M., Dachsbacher, C. and Pauly, M. Perspective accurate splatting. Proceedings of the Graphics Interface Conference, Canadian Human- Computer Communications Society, pp. 247–254.