Humanity Influenced Visualization Design for Aerial Sensor-based Visualization of Environmental Factors

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Abstract

The motivating perspective of this work is that visualization is a human endeavor as natural as human life is itself. This has profound influence on the way visualization is approached as the focus shifts away from any data-centric, visualization technique- or system-based foundations to one of human-centric visual perception, information perception, information acquisition and learning. This paper reports on part of a design of a visualization approach and system for deployments in wide-scope application areas of interest and which is guided by the Engineering Insightful Serviceable Visualization (EISV) model and is thus in the context of this human-centric perspective. The application areas are primarily loosely constrained environments, that are, environments for which available techniques such as computational modeling or fixed, location-based sensors are ill-suited. These environments have terrain, build or other similar features. An aerial drone-based sensor platform is proposed to sample environmental data in these environments. One of the included sensors on this platform is a LiDAR, a distance ranging sensor. The visual output of the LiDAR is primarily studied in this paper using the notions of iconicity and indexicality in the Peircean sense and guided by the EISV model. Several work-in-progress experiments that illustrate how the proposed system may respond are described.

Index Terms: Human-centered computing—Visualization—Visualization application domains—Information Visualization; Human-centered computing—Visualization—Empirical studies in visualization

1 Introduction

It seems typical that, within the field of visualization, visualizations are expressed mainly within a computerized perspective. The emergence of a recognized field is considered by many [8, 11, 37, 40] to have been the 1986 sponsored Panel on Graphics, Image Processing, and Workstations [31] by the National Science Foundation (NSF) of the United States of America. However, others [6] instead credit Tufte's 1983 book [48]. Yet, a broader viewpoint of contributory works, expressed in [23], reaches back to Bertin's 1967 work, to Tukey's 1977 work, along with Tufte's 1984 and Cleveland and McGill's 1988 work's. The claim of a recognized field itself needs closer examining. Certainly within the computerized viewpoint, it holds validity. But evidence abounds of thought-provoking visualization-related developments long preceding computerization. Corpora of visualizations in history exist [1, 2, 6, 17, 20, 32, 48, 50], many of which are published in visualization field-related venues. Some of the visualizations appearing in corpora are discussed in multiple sources, thereby achieving popularity at the same time, for example, the Fever Chart of Carl August Wunderlich [1, 10, 52]. The problem with corpora-based approaches is the lack of comprehensive representation across history; a single example provides a singular exposition but without much contextual quality. Alternatively, a comprehensive treatment across history, such as that about tree-based visualizations [30], or to a somewhat lesser extent, in-depth studies of specific visualizations such as that of Albrecht Dürer's (1471–1528) 1515 wood cut northern and southern celestial hemisphere charts [14] or the discussion of the c. 10/11th century graph plot of planetary orbits versus time [18], provides highlights of historical context. Other historical thought-provoking visualization studies stem from other fields, such as the 'truth-to-nature" characterization in [2] and the artificial boundary characterization between art and visualization in [45]. One may reach back to prehistoric times for additional thought-provoking studies. The sophistication of upper Paleolithic art includes figurative and abstract symbols, abstractness [46], visual devices for depth perception [9, 25] amongst others, and motion decomposition [5]. The perspective of visualization motiving this work is that it is not only an artifact related with computerization; but also, visualization is a human endeavor as natural as human life is itself: "...visualization abounds delimited by the space of individuality across human history." [14].

This viewpoint has profound influence on the way visualization is approached. It shifts the focus away from any data-centric, visualization technique- or system-based foundations to one of human-centric visual perception, information perception, information acquisition and learning. Much has been said in the visualization field about the goal of insight, indeed the quote attributed to Hamming and used in their 1962 writing [21] "The purpose of computing is insight, not numbers.", and more particularly the quote attributed to Card et al. [11] "The purpose of visualization is insight, not pictures." are motivational, at the least, in this regard. What makes this shift of focus profound however is its primary engagement with humanity. Insight is a part of humanity, but visualization centers on humanity itself; which may also be expressed as: humanity without visualization would not be humanity.

The Engineering Insightful Serviceable Visualization (EISV) model [13, 14] is designed with this viewpoint in mind. The model is an expressive but neither an operational nor a process model of visualization (e.g., it is compatible with the visualization pipeline but does not itself express the pipeline) concentrating upon issues of human individuality in visualization designs and engagements. The first paper [13] described morphological example applications of the EISV model. The second [14] informally extended the model and guided an in-depth analysis of the specific example of Dürer's (1471–1528) 1515 wood cut northern and southern celestial hemisphere charts. In this model, a particular visualization medium (e.g. an image) comprises <u>visualization components</u> each of which often graphically represents encoded answers $s \in S$ to sought-after questions $q \in Q$ for intended answers $a \in A$ (the difference between A and S is the former is what the human viewer wants to find out

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whereas the latter is the information available from visualization media). Visualizations components belong to type categories that abstract the degree to which a component supports encodings of S, for example a primary component directly represents $s_i \in S$, whereas some other non-primary type does not. The EISV model defines two tangible utilities of understanding and knowledge, each measured separately, in units of information chunks. The unit of chunks follow from Miller's 1956 exposition [33] as discussed in [12, 19] and refers to meaningful units of information in human working memory [12]. It follows in the EISV model, there are corresponding measurement functions and thus understanding and knowledge gain can be quantified although perhaps with uncertainties. The EISV model defines learning by a positive gain with insight as such a gain over a relatively short time, and conversely, confusion as a loss. The EISV model has associated a number of causes for confusion and thus, at present, its use as guidance for visualization design relies on avoidance of these confusion causes. The model not yet incudes causes for gains.

This highly simplified overview of the EISV model highlights only a few of the many aspects of the model; yet, is sufficient to convey an appreciation of the human-centeredness of the model. Individualistic elements include: the individual interpretations of S to A, the perception of the number and the type of visualization components, and the utilities of understanding and knowledge. Thus, for example, two people may engage with the same visualization media but interpret different numbers and types of components, thereby contributing to differing interpretations of sought-after answers A leading to differing understanding and knowledge gains or losses.

In this paper, the notions of the Peircean triad of iconicity, indexicality, and symbolicity are considered within the context of the EISV model. Brief introductory comments about this are included below; a comprehensive treatment is under development in [15] as the topic is both vast and complicated and is far outside the scope of this paper.

Charles Sanders Peirce's (1839–1914) [36] semiotics formulation describes three trichotomies, of which the triadic relationships iconicity, indexicality, and symbolicity of signs and symbols have been widely adopted in visualization [16, 34]. Each of these describe a relationship between the representation, an existing referent for that representation and its meaning. Simply described, iconicity refers to the identification of something by its visual likeness; indexicality refers to inferences of causes given effects in causal relationships; and symbolicity refers to negotiated meanings. Varying degrees of all three relationships may exist for any sign or symbol, for example a cartoon drawing of a banana may not be immediately recognized as a banana (lower iconicity), but may yet be indicative of something good to eat (higher indexicality). Iconicity scales have been developed [7]. In spite of the integral nature of the triad, in this paper, symbolicity is not dealt with.

The work described in this paper is preliminary, but already is significantly shaped by the human-centric viewpoint. The principal contribution is the demonstration that this alternative viewpoint of visualization can lead to effective, if not better, visualizations, even when dealing with constrained resource availability.

The paper is structured as follows. In the next section, the intended visualization application area is described along with our components of the proposed visualization system. The subsequent section describes the overall visualization interests followed, in the next section, by several work-in-progress experiments that illustrate how the proposed system may respond. Lastly, comments about how these experiments have been influenced by the human-centric focus of our approach appear in the conclusion section.

2 Intended Visualization Application Area and Proposed System

Our primary interest is in the visualization-based identification and tracking of airborne and waterborne substances in loosely-constrained environments. Our interest aligns with the recent research and commercial interest in the identification, monitoring and tracking of airborne (see for example [43]) and waterborne (see for example [29, 35, 47]) substances such as contaminates and toxins. We define these types of environments as having two principal properties: first, the physical environment influences the conveyance of substances from sources to points-of-detection, but which cannot in and of itself provide non-complex but sufficiently predictable downstream information; and second, sufficiently wide-open spaces such that single points-of-detection are unlikely to provide sufficiently useful information. Examples of these environments include air and water flows through terrain features such as large cave structures, canyons, and dense urban environments. Thus, computational-based approaches may suffer site-depended complex modeling as in urban environments [4, 53], or, detection locations may lack sufficient spatial resolution as in air quality monitoring which often relies upon few, sparse and fixed locations [3, 24, 28, 42] such as the monitoring sensors in Korea [26, 27]. Within such environments, we incorporate feature-based use-case modeling, for example, irrigation models, or, following the discussion in [28] near-residence spaces, traffic-residential regions, etc. These models provide contextual features, that is, features which can be related to and recognized from the visualizations.

The recent proliferation of affordable aerial sensor platforms (e.g., drone-based) coupled with low-cost sensors enables sensor deployment for environmental monitoring [24, 41, 42] in difficult-to-access terrain, for example, for forest inventory [44]. We target aerial, low-cost sensor deployments to provide mobility within loosely constrained environment spaces for multiple points-of-detection.

Expected benefits include better pollution monitoring for public health, considered an under-estimated issue in [42]; and, increased understanding of the influence that loosely-constrained environments have on airborne and waterborne substances, for as noted in [24], recent research in the general area of aerial-based applications remains focused on deployment issues but little in the way of expanding understanding of contributing factors.

To address the sensor-related requirements, we have developed the aerial sensor-based testbench visualization (ASV) platform which is composed of two almost-independent functional device assemblies: a drone itself functions as an autonomous flight unit providing both imaging function and aerial mobility to a sensor assembly. Separation between the drone and sensor assembly allows each to be focused upon its specific mission, and furthermore, allows either of the device assemblies to be upgraded or replaced independently.

The sensor assembly (which was assembled in our lab) consists of a Raspberry Pi 4 ("Raspberry Pi is a trademark of Raspberry Pi Ltd." [39]) microprocessor-based board, a battery supply, and multiple sensors currently securely placed on a 272.5mm (L) by 72 mm (W) by 88.5 mm (H) constructed frame weighing in at 443.2 g, see Fig. 1. The frame attaches to the undercarriage of the drone via a commercially available drone payload harness. The sensor assembly is mainly controlled and powered by the Raspberry Pi 4, with two micro HDMI® ports, four USB ports, wireless and Ethernet connections, and thus functions as an independent computer (HDMI® is a trademark or registered trademark of HDMI Licensing Administrator, Inc. [22]). In the base configuration, the Raspberry Pi 4 is connected to an external monitor via the HDMI port and other peripheral devices (keyboard, mouse, etc.) connected via the USB ports. The main power supply in this configuration comes from a USB-C™ ("USB Type-C™ and USB-C™ are trademarks of USB Implementers Forum" [49]) power supply. In its aerial deployment

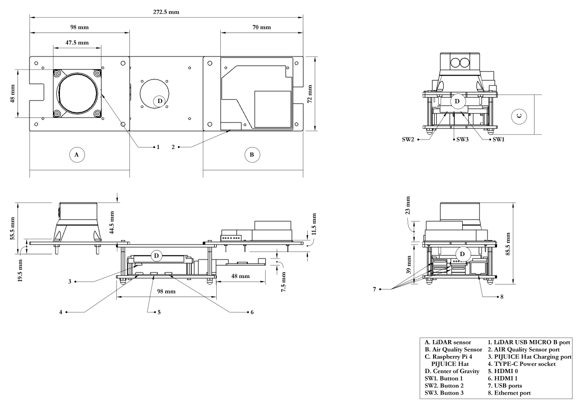

Figure 1: Sensor assembly schematic diagram.

configuration, power is supplied via the PiJuice HAT (PiJuice is a trademark of RAAmaudio U Ltd. [38]) connected to a 3.6 – 3.7 V, minimum 5000 mAh battery which powers the sensors through the USB ports. The sensors include: an SF45/B LiDAR sensor by Lightware Lidar LLC which can scan distances in the range of 0.2 m to 50 m, between 10 and 320 degrees horizontally up to 5000 observations per second; and an SDS011 PM2.5 air quality sensor by Nova Fitness Co., Ltd. Currently, water sampling is performed manually pending further technical assessment of the drone and sensor assembly.

The drone and sensor assembly provides multiple data streams, including, imagery, video, several air quality parameters, and distance ranging. Of these, and to maintain the scope of this paper, subsequent discussion concentrates solely upon the latter. The LiDAR stream consists of the raw data sampling of time-stamped two-dimensional polar coordinates of horizontal angle and distance that are then filtered to produce various types of output. The two-dimensional information sensing is, in part, due to resource constraints of weight, size and memory requirements of the output data set, and, in part, due to budgetary constraints that would be expected for low-cost product adoption. Thus, the raw data consists of multiple sets of distance observations per horizontal angle of the LiDAR sensor; the LiDAR sensor sweeps horizontally left-to-right, and reverses. We consider the rationale that the target area of observation is fixed and unchanging, and, assuming a fixed-point drone position (say as in hovering), the set of all distance measurements, per sensor detector angle, pertain to two fixed points, that of the source, and that of the target object. This is reasonably supported by believing that any small drone positional change due to hovering operations would have a low impact with respect to its assumed fixed point given the operational theater distances of 10-50 m.

The raw data sampling suffers expected errors such as noise, but we have found, also suffers extreme sensitivity at feature edges. The former is dealt with by typical outlier detection and removal algorithms. These include, in order, range checking within the sensor's stated specification range, a per angle binning (i.e., binning across all horizontal scans), a two-pass z-score filter to remove individual distance observations deemed outliers, and an optional manual removal of specific distance observations based on an manual assessment of the data set possibly including preliminary visualizations. This process generates a data set of one distance observation per angle, and thereby implicitly defines a piecewise linear connectivity when sorted by angle.

At this point, a toolkit of iconicity, indexicality and symbolicity abstraction algorithms (IISAA), which are based on the visualization design covered in the next section, are under development. The inputs are sets of piecewise linear connectivity coordinate sets. The algorithm used in this paper applies a simple one-point forward moving averaging smoothing of the piecewise linear set. The smoothing also addresses the feature edge sensitivity. The ParaView system is used to further manipulate and render the resulting data sets.

3 Visualization Design

Our principal focus in this work is the visualization of two-fold. First, the identification of sensor-based information along with its contextual information. The former refers to spatial-temporal air and water quality data along with specific substance tracking. The latter refers to environmental features that are recognizable in having either an influence on the data or its dispersion, or provide recognition about the environment. Features are considered at two scales: macro features are those recognizable within a whole scene; micro features are those which are not and thus needs be magnified (zoomed) or viewed in separate visualizations. Second, the exploration of relationships between the sensor acquired data in its contextual mise en scène.

Generally, in this application, questions are envisioned to fall into one of two categories: either directly about the environmental data, for example, what are the amounts of various toxins? or, directly about relationships between the environmental data and the features in its physical environment, for example, how are the toxins conveyed to points-of-detection? With respect to the scope of this paper, the former is of little interest here being of the quality of scientific data and primarily matched with appropriate scientific visualization presentations. However, the latter stimulates greater potential for discourse due to the variances of importance human viewers may place up the entities in the relationships, for example, referencing the earlier question of how are toxins are conveyed, one may be more interested in approximate or overall conveyance rather than specific detailed analysis in a specific area such as expressing a relationship between the feature of an irrigation channel and environmental data samples taken at multiple locations along the channel. A particular question may emphasize any aspect of this relation to varying degrees, for example, one might be more interested in understanding the topological layout of an irrigation channel and less interested in the details of the environmental data distribution, versus, another whose interest may be more exacting about whether some environmental data is caused by the irrigation channel itself. At the extremes, one may have complete interest in only features or in only data. In this paper, the discourse is limited to the former with respect to the latter, that is, the visual representation of feature space given some relation.

Loosely constrained environment features may be represented in various ways, for example, by images, point clouds, three dimensional models, and special symbols including labels. The choice of which depends upon two things: availability and suitability. Availability refers to whether the visualization system (alternatively, a designer's palette, say as used in painting, for non-computerized applications) supports the representation; one cannot display a point cloud if neither the data set nor system algorithms are available). Assuming availability, then a selection needs to be made based on suitability. Here, there is wide latitude in the visualization field about how to do this; for example, Ware [51] advocates many heuristics to support sound choices.

In this work, we consider the following. Sufficiently high-resolution imagery, point clouds and three dimensional models that are specifically focused upon features have potential to well capture the iconicity of the features. Each, however, may do so to varying degrees, for example, an image where the feature of interest is occluded or located at some distant point may suffer less iconicity, or, a point cloud or three dimensional model may not exactly represent a feature. In addition, iconicity may be decreased at lower resolutions. Along with iconicity, indexicality is also associated with the feature. In terms of feature recognition, an artifact presented in a visualization media may be indicative of some aspect of a feature, for example, an occluded object in an image cannot be recognized, yet, observing its shadow may alert the viewer about that object. A range of iconicity and indexicality values inherent in feature recognition exist. Each also suffers limitations when incorporated into visualizations, for example, images suffer two-dimensional planar insertion in visualization often textured mapped to planes, may be difficult to correctly orient or properly light, and may not provide three dimensional scene viewing experiences.

High iconicity rendering of features would be primarily intended for cases where question-based emphasis is upon the features in interesting relations; but may be presented with lower iconicity value were the emphasis upon the data (and in the extreme case of a question relating only with the data, the feature may be removed from the visualization altogether). In the visualization field, such operations as blurring, fisheye views, etc. seek to present useful information at varying levels of iconicity.

The research question emerges: to what iconicity and indexicality value levels are needed for feature recognition so as to effect insight as defined by the EISV model in the context of interesting relations where some emphasis is placed on the features. This forms the specific focus of the experiments described in the next section.

4 Experiment

Recall from previous discussion, a horizontal scan is obtained from the LiDAR sensor. When drone mounted, may have two characteristics. First, the aerial platform may be stable, unmoving, and with no tilt, thus the scan has a known height. Second, the platform may be tilt between two successive scans, thus the height is not known. Two experiments, each concentrating on these characteristics, have been conducted as simulations of aerial LiDAR-based sensing. The purpose is to explore the visual issues related with iconicity and indexicality of feature recognition; thus follows from the aforementioned research question.

4.1 Hallway Experiment

The sample space is a hallway with four doors, two on each side (not symmetrically aligned), and a back wall comprising window frames approximately half-way up at varying distances set a bit further than the wall and a chair (placed backwards to the LiDAR sensor). Thus, the scene consists of the macro features of doors, chair, and wall versus window frames; and the micro feature of the varying distances of the windowpanes. Certain distance measurements were conducted manually to check and calibrate the sensor.

LiDAR samples were taken as follows. Multiple horizontal sweeps at 30 sweeps per second for two minutes, extending from 45-degree angles were conducted at each at the five predefined heights of 90 cm, 97 cm, 106 cm, 114 cm and 120 cm such that the lowest intersected the chair and wall and the upper two intersected only the window frames; all intersected the doors on the side.

A top plan view of the LiDAR acquired data, with minimal filtering (that is, distance averages determined for each angle for each scan and no outlier removal) is shown in Fig. 2. This provides near-to-original data for analysis, but due to increased numbers of points, each point needs to be shown via small-sized glyphs accounting for difficulty in viewing the chart. Macro features include as follows. Features A – D represent the doors with the door width exemplified by the outwards angled measurement (see Aa – Ab of approx. 96 cm) followed by a sharp inwards angled measurement (notated at the feature label locations of approx. 21 cm). For comprehensiveness, other distances are also noted on the diagram. Feature E represents the chair. Feature F represents the wall and feature G, the window frames (of approx. 20 cm separation). The micro features Ga, Gb, and Gc represent the varying distance separations of the window frames.

The macro features are again visible in the fully filtered image 3, although feature D may not be well identified. So far, this discussion has dealt with the issue of indexicality of the representation. The image shown in 4 provides an immersive view of the filtered LiDAR data along with an image of the far wall with windows, cropped and scaled accordingly. The use of the image provides iconicity for the features: it is more easily noticeable that the bulge in the center is due to the chair, and that the wavy lines are due to the window features.

The experiment successfully meets its objectives. First, indexicality of macro features is usable given feature description; for example, given the description that there are doors on each side, one can identify those doors. Second, the incorporation of the image

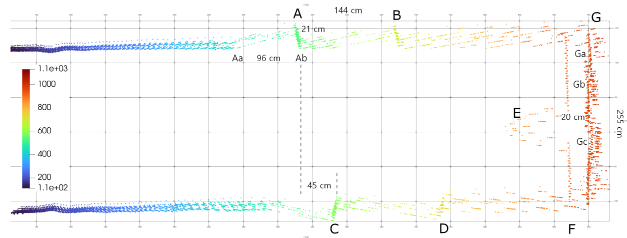

Figure 2: Top plan view (parallel projection) of LiDAR acquired data after filtering.

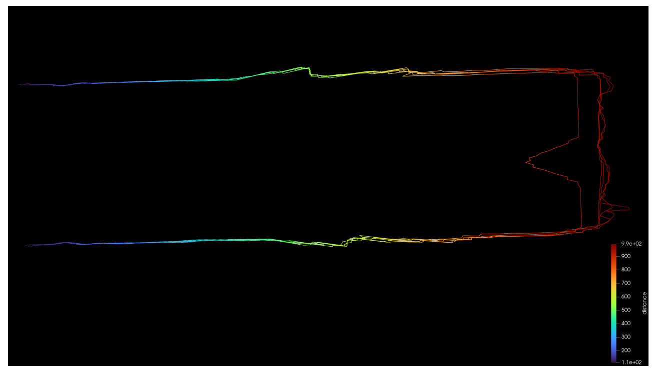

Figure 3: Top view (parallel projection) of LiDAR acquired data after full filtering.

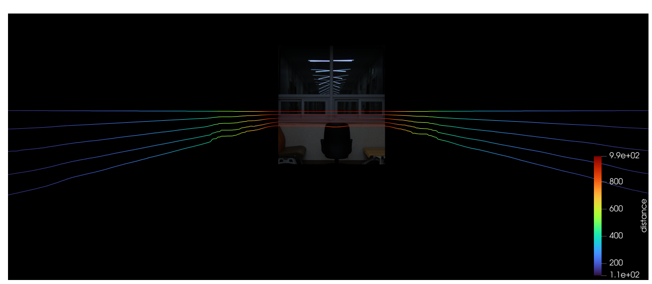

Figure 4: Front view of LiDAR acquired data on an camera image of the wall with window frames.

Figure 5: Agriculture irrigation channel, location 1

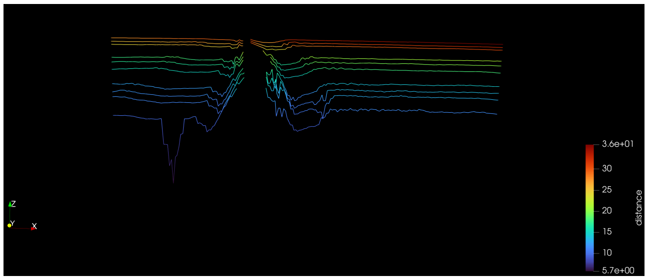

Figure 6: A LiDAR visualization of location 1

Figure 7: Agriculture irrigation channel, location 2

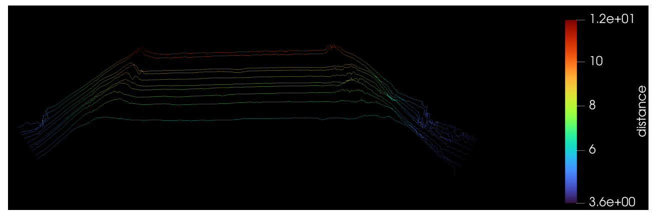

Figure 8: A LiDAR visualization of location 2

provides increased iconicity, thereby replacing feature description, for example, there is no need to specify the description that there is a chair. Third, there is a balance between encoding indexicality and iconicity, for example, there is no need to provide side wall images as the door features are identifiable. Admittedly, the macro feature D door is problematic for indexicality only presentation, and thus the system may introduce an image of that section of the wall to address it.

4.2 Agriculture Experiment

The sample space are agriculture irrigation channels. Two distinct locations were assessed, see Figs. 5 and 7. The first is a narrow but long channel, the second, a wider but shorter channel. Corresponding, the LiDAR sensed images are, Figs. 6 and 8. In this experiment, the LiDAR height was held constant (see Fig. 7) but each scan occurred at a different angle of tilt. It therefore is a two-dimensional model. Currently, we are further developing the IISAA toolkit to address issues relating with this type of data set. That being said, in these figures, two post-processing operations have been performed: first, transform the height of each scan line by increments and second, perspective from the eyeball of the LiDAR. The resulting images therefore have some perceptive correspondence with the terrain. But this simple transformation introduces artifacts into the visualization, the worst of which appears to be the inversion of height perception, the channel becomes a hill. Nevertheless, it is interesting note that, in terms of the theory presented in this paper, the indexicality nature of the channel as a hill exists and it is easy to see that correspondence with the actual image.

5 Conclusion

The viewpoint that visualization is a part of human nature means that visualization is connected and inseparable from human experiences and endeavors. Evidence for this abounds and it should no longer be a matter of debate. What is up for debate is how visualizations may be designed with this viewpoint in mind: visualizations in the sense of computerized or non-computerized, contemporary or future or past, scientific or information. It remains unclear what and by how much, the exact influence of this viewpoint has on visualization design and analysis: hence the profoundness of influence.

For the most part, typical LiDAR presentations found in academics and industry rely upon large, dense, point clouds that emulate a three-dimensional model of the scene. And there certainly is much merit in doing so, relying on its iconicity values. However, the kinds of visualizations considered in this paper in the experiments with LiDAR acquired data sets presented a very different type of visualization design. Beyond the obviousness of accommodating resource constraints, the design utilized themes from humanity; namely, our brain's capabilities as modeled by the Engineering Insightful Serviceable Visualization model together with the Peircean-based iconicity, indexicality and symbolicity triad as applied herein. Successful visualizations have been demonstrated; albeit also indicative of substantive research and development to improve such to a level of viability.

An aerial sensor-based testbench prototype system for air and water environmental applications is also presented in this paper. The sensor assembly, described herein, provides environmental data along with images/video and LiDAR data sets. The testbench enables the design and implementation of a visualization system based on the human-centered viewpoint expressed in this paper.

During the work in preparing this paper, we uncovered a number of challenges that motivate us for future work. The aerial platform has high degree of error sampling due to its motion, and we must contend with mission setup issues. The LiDAR sensor suffers several technical limitations. And, not to mention, drone licensing and operation requirements that both hinder and limit our deployments.

Acknowledgments

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