FieldView: Immersive Visualization and Data Fusion for Situated Analysis in the Field

ABSTRACT

Data collection and analysis in the field is critical for operations in domains such as environmental science and public safety. However, field workers currently face data- and platform-oriented issues in efficient data collection and analysis in the field, such as limited connectivity, screenspace, and attentional resources. These issues substantially degrade analysts abilities to integrate data and environmental contexts into analysis and decision making, inhibit local and distributed team coordination, and prevent analysts from fusing data from multiple sources and evaluating the quality of collected data while in the field. We address these challenges by developing a prototype system leveraging mobile devices, cloud-based storage and fusion, and augmented reality (AR) visualization. We conducted a formative evaluation of our prototype with 10 people from five domains to explore how situated analyses enabled by this approach facilitate their data entry, visualization and analysis needs in the field. We use these results to synthesize guidelines for future field analysis systems and refine our prototype to support critical use cases for situated field analysis. Our findings suggest the potential for immersive technology to bridge critical spatial and temporal gaps in field analysis.

ACM Classification Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous; See http://acm.org/about/class/1998/ for the full list of ACM classifiers. This section is required.

Author Keywords

Immersive Visualization; Field Analysis; Augmented Reality; Mobile Data Collection

INTRODUCTION

Data-oriented decision making is transforming practices in a broad variety of domains. Applications in earth science, geology, and emergency response all leverage data collected in the field to help describe the state of complex environments. Quantifying these environments allows analysts to model the changing state of the world over time and to share information across teams to increase situational awareness and deepen scientific and operational understanding. However, current practices for working with data in the field rely heavily on

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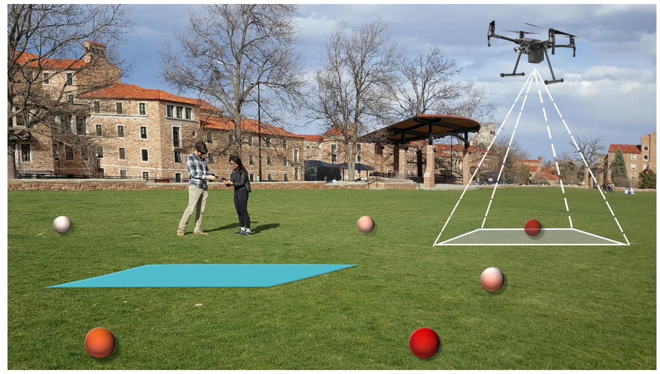


Figure 1. FieldView enables analysts to collect and explore data fused across various sources within the contexts that data describes to support improved *in situ* data analytics and decision making.

decoupled solutions that separate data analysis from the spatial and temporal contexts that data describes: data is collected in the field but analyzed elsewhere, such as in operations centers or remote laboratories. This separation can limit field analysts' abilities to integrate current data into analysis and decision making practices, introducing significant time and efficiency costs.

We address this challenge by exploring how mobile and immersive technologies can help bridge spatial and temporal gaps between data collection and analysis in fieldwork. Specifically, we explore how we can couple these technologies to increase contextual and situational awareness in field analysis practices in order to improve data collection, sharing, analysis, and decision making by better connecting field analysts with their data. We focus on how mobile data collection, cloud fusion, and augmented reality (AR) visualizations enable analysts to visualize data as it is collected, allowing analysts to integrate contextual information about the immediate environment into data interpretation. Our approach fuses data from multiple sources to provide field analysts with access to new and existing data from other teams in the field, archival sources, and autonomous sensors. Analysts can then leverage at-a-glance mobile visualizations or immersive interactive visualizations to develop new hypotheses, identify potential errors or gaps in coverage, and adapt operational practices while in the field.

Current practices for fieldwork require analysts to first preplan their operations based on archival data from both previous collection efforts and archival data streams. Analysts then collect new data either on mobile devices or in field notebooks, physically transport data to a central location to synchronize with other sources, and replan subsequent collection efforts and operational practices based on the newly revised data. This workflow decontextualizes collected data from the environment, prevents analysts in time-critical situations from reacting to new data, and obscures possible errors in data collection. These challenges are exacerbated when data comes from multiple sources: analysts have limited access to additional data collected from other field teams or independent sensors. Our approach leverages cloud datastores to fuse data from multiple sources as data becomes available, leveraging both local and global data storage to overcome connectivity limitations in the field. We additionally extend existing practices for field data analysis by allowing analysts to conduct rapid inference using mobile visualizations or immersive embedded data visualizations that contextualize data within the physical environment and leverage more visual space to support nuanced analyses. This workflow increases contextual awareness to improve data-oriented operational goals, provide real time data quality assessment, and support synchronous operations between field teams.

We implement this approach in FieldView, a mobile data collection and visualization system designed to bridge the spatial and temporal gaps between data collection and analysis in the field. We developed FieldView in conjunction with field analysts in domains ranging from forest ecology to public safety. We discuss how our approach addresses several challenges in field analysis and refine our approach to accommodate field analysis using observations from ten domain experts. We demonstrate our approach using three scenarios for field analysis inspired by our discussions with field analysts unsupported by existing approaches: data-mediated teaming, data quality verification, and on-demand visual fusion with external sensors. By coupling mobile data collection and immersive analytics, our approach can foster improved data collection, interpretation, and decision making by providing field analysts with increased access to incoming data and allowing analysts to interpret that data with respect to aspects of the environment only available in the field.

Contributions: We design a novel data collection and analysis prototype focused on enabling critical decision-making in the field. Our prototype extends on prior field data collection systems based on a survey of field analysts in domains ranging from environmental science to aerial firefighting. We leverage immersive visualizations to improve sensemaking in the field for scenarios not well served by conventional mobile technologies. Our use cases introduce novel visualizations and workflows that address gaps in field analysis technologies to increase operational efficiency in the field.

RELATED WORK

Bridging the gap between data collection and analysis for field tasks requires both understanding how contextual awareness can inform analysis as well as the technologies and approaches that might enable such a solution. We focus on developing methods that allow field analysts ready access to important information to improve the quality of their data collection practices, interpretation, and operational decision making. We build on preliminary work in situational awareness and contextual computing in HCI as well as mobile and immersive analytics techniques to support these goals.

Contextual Awareness in Emergency Response

One limitation of current practices for analyzing field data is a lack of contextual and situational awareness (SA). Technologies may consider many forms of SA. For example, Endesley et al. models three hierarchical phases of SA in dynamic systems [13]: (1) perceiving elements in the environment, (2) comprehending the situation at hand situation based on disjoint elements, (3) projecting the future status of a situation based on a knowledge of both the status and dynamics of current situation. Systems can increase SA across these phases by designing for change detection, preparedness for interruption, goal reorientation, and detection of missed changes [23].

Increasing SA is especially critical in technologies for highly dynamic situations where new data frequently changes operational strategies, such as search-and-rescue and emergency response. For example, Cao et al. found that people trusted their own situated understanding over the advice of agencies in predicting wildfire spread [6]. Kim et al. increase field responder SA using mobile devices to visualize location-based data on mobile devices, allowing users to "see through the fog" [25]. While these solutions increase awareness of areas invisible to users, they also require divided attention and map potentially complex data to a limited visual space. We address these limitations by exploring how augmented reality may supplement existing mobile data entry and visualization technologies, bypassing the need for device-to-environment context shifts by situating data directly within the physical environment to increase contextual awareness.

We ground our exploration of this space in visual analytics systems. These systems allow analysts to bring domain expertise and contextual awareness to data exploration and decision making by allowing analysts rather than algorithms to synthesize insights from available data. For example, Chan et al. makes use of multiple spatially aware displays to increase SA in a central command center [7]. Visual analytics systems may support the information needs of these domains by reducing reliance on verbal/radio communication, integrating information from multiple sources, and combining both streaming and manual data entry [18] as well as improving collaborative teaming [26]. These technologies aim to provide domain experts with sufficient knowledge about the global state of the operational environment to make data-informed decisions in dynamic environments. However, these solutions generally target a remote operator with a global view of the task at hand but limited understanding of the context of field data. We instead aim to put these visualizations in the field, considering how mobile technologies and immersive visualization can support field analysis needs while mitigating limiting factors of current mobile approaches like divided attention and limited display size.

Immersive Visualization for Fieldwork

Augmented reality (AR) can enable contextually-aware data analysis by outfitting the physical environment with virtual content [45]. For example, ubiquitous analytics techniques leverage data collected in disparate environments for situated analysis [12]. Such techniques include mid air displays for map navigation [10] as well as cross device displays for collaborative visualization [2]. Systems have used AR to directly annotate the environment with data for applications in construction and architectural oversight [20], energy aware smart homes [21], building and manufacturing [30, 3], and situated learning [40, 9]. For example, visualization overlays on proximal referents can help highlight previously searched paths in search-and-rescue [45]. Other systems use AR to highlight critical information along 3D surfaces including rock folds [17], mammograms [11], and physical bodies [19]. These techniques offer interactive methods for engaging with spatial data that may outperform other mobile technologies such as tablets [1].

In fieldwork, these technologies hold promise for resolving the "field map shuffle" where researchers constantly reference several potentially out-of-date sources for geographical information [35]. For example, McCaffrey et al. theorize how portable stereo visualization might enable field-based visualization for complex geospatial models [31]. Pavlis et al. extend this vision to suggest how immersive visualization for may improve map synthesis [35]. However, these efforts offer purely theoretical insight into such designs. More recent works have begun to explore preliminary designs for targeted analysis problems in field research. For example, Gazcón et al. allow field researchers to augment an existing view of mountains with lines highlighting geological folding patterns [17]. Ramakrishnaraja et al. visualize sensor data in AR to increase SA for oil and gas workers [37]. However, these systems focus on a narrow set of well-defined analysis tasks and do not consider how field analysts can integrate incoming information or how these technologies may support broader investigations. We extend these ideas to support holistic situated analysis for field domains, bridging data collection and analysis and developing a systematic understanding of how immersive situated analysis techniques may better support data-oriented fieldwork in a broad variety of domains.

Mobile Data Collection and Visualization

Mobile devices support portable data collection and sensing across a broad variety of applications [16, 38, 28, 33]. Using mobile devices for data entry can enhance data quality over traditional physical map-based methods [39, 15]. For example, Pascoe et al. demonstrate that user interfaces for field data collection must minimize the amount of attention needed to use a device while maximizing benefits of contextual awareness [34]. Tomlinson et al. show how mobile devices can support distributed data collection efforts [41]. ESCAPE provides a middle-ware layer for exchanging information between mobile devices in emergency response [42]. The studies show that simplicity and contextual awareness are critical components of successful field data collection.

However, analyzing data on mobile devices can be difficult due to the limited display, storage, and computation capabilities of these technologies [8, 29, 32]. These challenges are exacerbated in field scenarios and extended to include other challenges such as decision time and privacy concerns [14]. Solutions like Siren leverage context-aware paradigms to support peer-to-peer messaging based on environmental triggers, choosing to reduce cognitive load through automated analysis based on contextual data [22].Though mobile technologies have limited display size and resolution, they readily support location-based visual analysis, including mobile tourist guides [4], overview-detail map visualizations [24] and mobile device-mediated navigation tools [5, 36]. These visualizations generally focus on a few critical data attributes in order to increase analysts' abilities to get critical information at a glance [44]. We leverage simple visualizations with location-based data collection and analytics in order to support data-oriented fieldwork across a number of different domains. We combine these approaches with immersive AR visualizations to enable deeper engagement with data and blend data and context to tightly couple data collection, exploration, and context for field applications ranging from forest ecology to public safety.

REQUIREMENTS ANALYSIS

Our objective is to provide an integrated platform for situated analysis in the field that enables field analysts to collect and analyze data within the spatial and temporal contexts that data describes. To characterize the problem space, enumerate the anticipated requirements of such a system, and identify limitations in existing approaches, we conducted a set of preliminary interviews with four field analysts: one in public safety, two in wildland fire, and one geological science.

In these interviews, analysts identified three limitations with current mobile-only solutions that prevent them from adequately leveraging data as part of their field practice: divided attention, small form-factors, and reliance on operational centers. Analysts noted that current mobile-only solutions require them to interrupt their practices to engage with data on mobile platforms and again to integrate context into their analysis, similar to the hazards of texting and driving [27]. The small screen space and strict touch-based inputs of current mobile devices often limited their abilities to draw substantive conclusions about data. These limitations led to heavier reliance on external analysis at an operations center or field site. However, limited connectivity can cause substantial delays and information loss in streaming data between the field and operations centers. As a result, field analysts either operate agnostic of field collected data, use stale data from daily preplanning, or rely on strictly verbal communications relayed from the operations center. Operations centers additionally lack the contextual awareness of field analysts, while field researchers lack the awareness of multiple fieldsites granted to remote operators.

We synthesized these interviews to formulate a set of requirements for field analytics tools:

R1–Offline Data Collection: Field analysts often work in remote locations with limited to no connectivity. Most field analysts collect and log data in the field, store that data on thumbdrives or other portable media, and fuse that data with data from other efforts back at the operations center. Being able to fuse and visualize new data in real time would improve field analyst decision making with respect to team operations when connected and provide timely perspectives on their current situation when offline.

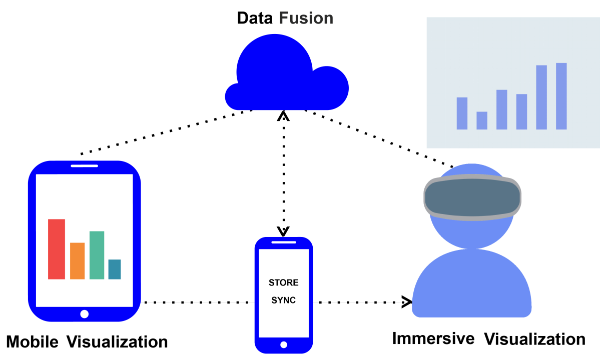


Figure 2. An overview of our initial FieldView system–data is collected and merged with cached data on a mobile device and synchronized with a cloud data store whenever the device is connected. Cached data can be viewed at a glance on the mobile device or explored in a portable immersive headset like the Samsung GearVR to enable deeper analysis and increased contextual awareness.

R2–Merge Environmental Context & Analysis: Data collection in fieldwork attempts to capture important aspects of an environment to build a broader understanding of the changing environments, functions, and scenarios present in the world. However, not all aspects of an environment can be quantified and captured in a database. As a result, effective tools for situated field analysis must allow analysts to fluidly combine information from the environment with data analytics to increase contextual awareness and enable enriched decision making.

R3–Mitigate Information Overload: While in the field, analysts often multitask. They therefore need to get a quick sense of how their data fits into the current context without having to spend significant amounts of time immersed in the data. As a result, situated field analysis systems should balance specificity and flexibility: analysts need to rapidly generate important insights without incurring substantial cognitive overhead to build these insights.

R4–Use in Outdoor Environments: Operations in outdoor environments require analysts to carry any necessary equipment. Field analytics systems must be sufficiently portable as well as robust to changes in lighting and to use when wearing bulky equipment like gloves.

These requirements, while integrating concerns from disparate domains, closely echo prior guidelines developed for firefighting applications [14]. We used these design requirements in conjunction with findings from prior work to develop FieldView, a prototype system for situated analysis in the field.

FIELDVIEW IMPLEMENTATION

We used these design requirements to construct the FieldView system for situated data analysis in the field (Figure 2). Analysts can input data on mobile devices to a local database (**R1**). When connection is available, the cached database synchronizes with a cloud data store and fuses incoming information from external teams and sensors using geolocation data. Analysts can then visualize cached data at a glance on their mobile device or load the data into an immersive interactive visualization (**R3**) using either a portable see-through display (e.g., Fig. 7) or the mobile device's camera (e.g., Fig. 4), analysts can visualize that data in context or elect to have full visualizations persist within their field of view. We implemented our original prototype using an Android device and the Samsung Gear VR headset. This form-factor allowed us to deploy our system using highly portable hardware supporting basic interactive functionality (**R4**). We have extended our application to also run on other headsets, including the Microsoft HoloLens.

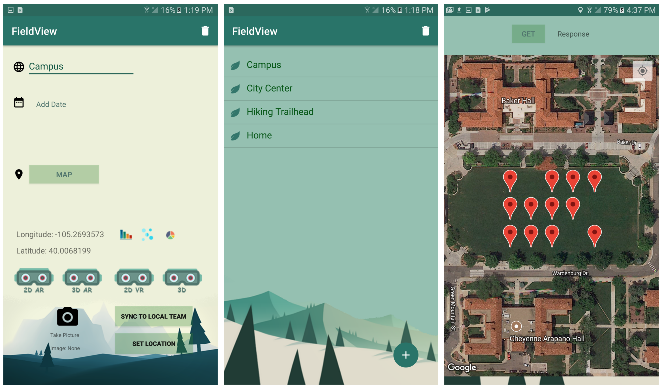
Data Collection

While data collection occurs in the field, most field-related decisions are currently made in a command center, separately and asynchronously from data collection. This separation may result in issues like data loss, insufficient coverage or quality, and extra time and monetary costs of returning to the field. Prior efforts have shown that mobile data collection can provide powerful distributed collection practices [41, 34]. We build on these efforts to consider both distributed teams and limited connectivity in FieldView to improve fieldwork efficiency and bridge the gap between field workers and decision makers.

While cloud solutions provide powerful computational tools, field analysts typically avoid cloud solutions due to limited connectivity: data cannot always be streamed to and from the cloud device. Instead, analysts currently stream data to portable drives, local spreadsheets, or use traditional paper methods. We developed an Android application to collect and store field data using a two-phase process.

Phase One–Local Data Storage: Our Android application draws data directly from a local datastore housed on the mobile device (a SQLite database in our implementation). Before analysts enter the field, they can synchronize this datastore with requisite existing data to support active objectives, such as data from prior objectives, preplanning, or relevant archival sources. Analysts manually input new information through the application's data entry interface, with entry forms autopopulated using the columns of the local datastore (Fig. 3a). New data added in this interface is immediately synced to the local datastore. The application's list view allows analysts to see these manual entries (Fig. 3b). Considering heterogeneity of different field workers and limited time of data collection process, we standardized the user interface of this application based on the local datastore using a field notebook style interface. The use of the local cached template provides consistency in data collection practices across disparate teams.

Phase Two–Cloud Storage & Fusion: When a given mobile device regains connection, the local datastore synchronizes with a cloud datastore containing data from archival sources, earlier efforts, relevant coordinated efforts, and sensor collection. The datastore fuses this data based on geospatial location data collected by the mobile device's internal GPS. The synchronization first pushes new data to the cloud datastore then refreshes the cached data in the current datastore. This caching process allows analysts to retain updated information even once they lose connectivity. Further, the synchronized



(a) (b) (c)

Figure 3. Features in original prototype on mobile device: (a) Interface for data collection in the field and (b) corresponding list of local data points collected in the field (c) An example interactive visualization displayed on mobile based on remote server data.

data is flagged in the application list view such that the analyst can track how fresh the available data is.

We implement our cloud datastore using a MySQL database hosted on a standard web server. While our implementation provides no pre-processing of the data prior to transmission, we implement our dataflow using standard HTTP message passing. For especially large datastores, revised versions of this system could integrate domain-specific wrappers and fusion algorithms that precompute relevant data for caching based on geolocational prefectching and the needs of the domain and objective.

Situated Visualization

While our mobile data collection platform allows analysts ready access to data, current solutions for analyzing that data in the field are limited: our interviews suggested that analysts have no reliable methods of actively engaging fresh data in the field. However, recent advances in mobile and immersive analytics (e.g., [12, 45]) may allow analysts to analyze data as it becomes available to increase situational awareness and to ground those analyses within the contextual awareness provided by the active environment (**R2**). FieldView allows analysts to explore available data using a set of conventional visualizations familiar to analysts (**R3**) visualizing user-selected data dimensions through two different workflows: *mobile visualization* and *immersive visualization*.

Mobile Visualization: In current field study, data quality assessment and replanning largely depends on the expertise and experience of field workers to interpret. As a result, analysts need to quickly access information during data collection to ground data-driven decision making. Our mobile visualization allows analysts at-a-glance access to cached data on the immediate mobile device. Analysts select a set of target data dimensions and visualize those dimensions using a map, bar chart, or scatterplot. These simple designs, one of which is shown in Figure 3c, adhere to analysts expressed needs around quick, "sanity check" analyses tailored to the limitations of mobile devices [44].

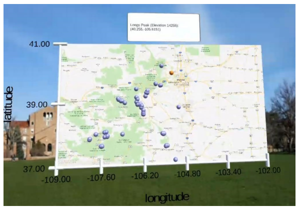
Immersive Visualization: Mobile visualizations still suffer from divided attention—analysts must direct their attention away from the environment in order to analyze data—and limited screenspace. To overcome these limitations, analysts can load data into FieldView's immersive visualizations and view the resulting data using a portable head-mounted display synchronized with the mobile phone. In this mode, analysts can interact with collected data in context by augmenting the physical environment with visualizations of collected data. This augmented approach increases the apparent screenspace and helps retain situational awareness by allowing analysts heads-up access to visualized data as well as to the context of the world around them.

FieldView allows analysts to readily load immersive visualizations that use the Samsung Gear VR using two different modes: a billboarded analysis view and a contextualized 3D view (Fig. 4). These visualizations query the remote datastore to access information collated from all on-going collection efforts, using the cached data as a backup. In interviews with collaborators, we elected to only show augmented reality visualizations over virtual reality representations due to the potential for AR to bind data and context [45]. Additionally, we understood collaborators to be more interested in augmented reality than virtual reality, due to its ability to keep the retain environmental context, in line with **R2**.

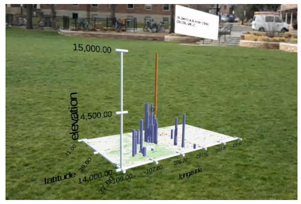
Analysts interact with objects using a gaze-based raycast cursor to select objects and the Gear VR's directional pad to select and pan. Selecting a datapoint provides access to details about that data on demand (**R3**). Moving the visualization using the D-pad allows analysts to relocate the visualization in-place to adapt for the limited tracking capabilities of the Gear VR and to move the visualization within the field of view to better contextualize the data. To help analysts contextualize data from their local environment, visualizations can encode remote data values using blue values (or green for stale data when connectivity is unavailable) and data recently added by the analyst in red (Fig. 4a and 4b). Alternatively, the visualizations can provide general overviews of existing data. For example, Fig. 4c and 4d encode time using a sequential heatmap, with more recent wildfires in darker red. Note that while our example figures are 2D, FieldView provides stereoviewing of 3D visualizations.

EVALUATION

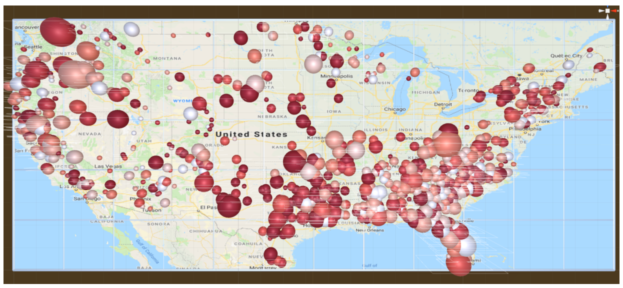
We conducted a formative evaluation to understand the potential for FieldView to enhance field data practices in semi-structured interviews with ten field analysts using FieldView in a controlled environment. Interviews ranged from 1-2 hours and were divided into five different sessions. Six interview subjects were in emergency response domains (five in aerial firefighting and one in Public Safety), two were earth scientists working in forest ecology, one was a computer scientist using field data for climate modeling, and one specialized in robotic sensing with drones. Our interview questions focused on analysts' backgrounds; current use of data in the field including collection, storage, and analysis tools; responses to the prototype; and envisioned uses for field analysis based on the



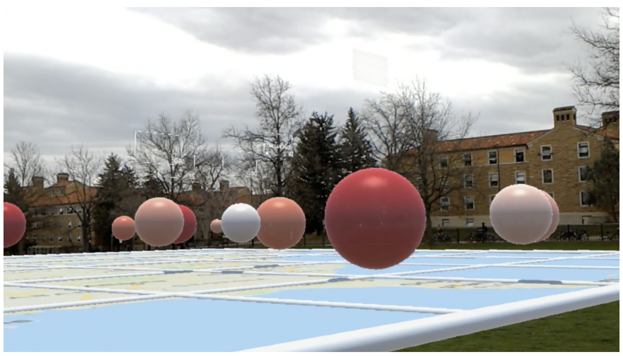
(a) Billboarded map of altitude data



(b) Contextualized 3D bar chart of altitude data



(c) Billboarded map of archival wildfire data



(d) Contextualized map of archival wildfire data

Figure 4. FieldView allows analysts to access data using both billboarded 2D views for rapid analysis and contextualized 3D views to increase contextual awareness. These figures use altitude data about critical structures (a & b) and archival spatiotemporal data about wildfire size (c & d, color maps to time while point size maps to the size of the affected area).

functionality showcased in the FieldView prototype. Interview questions are available in the supplemental materials.

We analyzed the transcribed interviews for common themes emerging across domains to identify common practices in field analysis that systems like FieldView can support. We found that, though our interviewees ranged greatly in technical expertise and domain focus, they identified several common themes in potential uses for FieldView. In this section, we discuss these themes, how analysts envision using FieldView to support needs expressed in each theme, and how our implementation could be extended to better support field analysis.

Reliance on Location-Based Data

Analysts responded positively to FieldView's emphasis on geospatial data. Though different groups leveraged different types of data, analysts generally stressed the importance of location-dependent data in the field. For example, analysts commonly used image data labeled with geospatial locations, using both raw images and orthomosaics generated by fusing data across several locations to assemble surface or terrain models. Location data was regularly sampled from specific geospatial regions. For example, earth scientists subdivide a fieldsite into regular grids and collect one datapoint per gridcell to ensure sufficient sampling. Aerial firefighters use land ownership data defined by property boundaries to guide their operations. Climate scientists and earth scientists often leverage sensor-based or manually entered environmental data such as temperature, humidity, glacial velocity, and tree diameter to reconstruct an environment and model spatio-temporal patterns.

The focus on spatial maps in FieldView's immersive visualizations allows analysts to visualize data about the full space of operations. The simple visualizations enabled appropriate levels of analysis while providing opportunities to dig deeper into the data through interaction. However, analysts wanted a closer coupling of the visualization and environment—they wanted to see how data could be more tightly interwoven into the physical space. This coupling could improve the integration of contextual awareness into data analysis and better support operational decision making.

Teaming under Limited Connectivity

All participants noted that they conduct field operations in teams. Those teams can be distributed over a wide space (e.g., around the perimeter of a wildfire) or co-located in a local environment (e.g., collecting tree cover measurements around a specific fieldsite). Currently, data sharing between teams is done either through direct communication in co-located teams or by radio commands from an operations center for distributed teams. None of our interviewed teams had workable solutions for sharing and collaboratively analyzing incoming field data across teams.

Participants were excited about the potential of FieldView to support teaming in both co-located and distributed environments. In co-located environments, data sharing would allow for consistency checks across team members. For example, our simulation analyst noted an incident where two teams at a fieldsite calibrated their sensing equipment differently, leaving their data unusable. Shared data between these team members would allow for at-a-glance identification of potential anomalies arising from such inconsistencies within teams. For distributed teams, aerial firefighters noted that recent advances have allowed them to share basic geocoordinates alongside radio transmissions to help improve situational awareness, but noted that these techniques are extremely limited. They remarked on how labeling data values based on team entry in FieldView's map visualizations would significantly expand their awareness of the state and progression of a fire and, combined with existing radio communication, let them more readily adapt their operations through data-mediated communication between teams.

While participants noted the utility of FieldView's two-phase data synchronization, they cited limited connectivity as a current barrier to using FieldView for teaming: cached data is bound to a single device, while cloud data requires connectivity. Even co-located team members may struggle to share the data necessary for informed decision making. Further, cloud transmission may not always be desirable due to privacy concerns around image data and other sensitive information. One solution noted by aerial firefighters leverages a high-range portable router to collate data from co-located teams, similar to the peer-to-peer infrastructure in Siren [22]. Field analysis systems may be able to use these technologies to improve data sharing among local teams as well as mitigate privacy concerns introduced by cloud-based solutions.

Data Quality Validation

Ensuring high quality data coverage is critical for effective field surveys. Analysts noted that data collection errors often force them to return to the field and repeat data collection if found while at the field site or to discard large amounts of data if undetected until lab analysis. For example, our climate modeling subject remarked that mistakes in data collection for glacial research were unresolvable as they required flying equipment back to remote locations in Greenland or Antarctica. Earth scientists remarked that measurements of tree circumference taken at chest height could introduce substantial variation depending on the researcher. While these inconsistencies are easy to resolve, they are impossible to detect in the field. Analysts currently validate most data by "looking at the size of the file and saying 'that looks about right."'

Participants felt that the depth of analysis provided by FieldView visualizations would significantly improve data quality validation. Analysts saw FieldView's abilities to provide immediate insight into collected data as a means for quickly identifying data quality errors. They noted that these visualizations would save substantial time and money in field operations. They found the simplicity in the chosen visualizations would allow analysts to quickly note where errors occurred using familiar representations and to verify consistency by exploring high-level patterns in existing data. Quick glances at the mobile visualizations would provide a sense of data coverage, while the immersive visualizations would allow analysts to dig deeper into potential anomalies and compare those variations side-by-side with the conditions of the environment to help explain and remedy any issues in the data.

One limitation in the current approach was the lack of focus on where quality issues might lie. While most field quality issues are difficult to detect automatically, others, such as missing data, can be brought immediately to analysts' attention. Further, field analysis technologies should allow analysts to update their goals and operational strategies as a function of the quality and completeness of incoming data. Analysts recommended that field analysis systems more deeply consider how embedded visualizations might aid analysts in quickly identifying problematic areas in data collection to increase data collection quality and efficiency.

Data Fusion Across Perspectives

Field analysts generally rely on archival data to plan the day's operations, such as recent environmental surveys or topological maps. Analysts reported that FieldView's visualization systems offered enormous potential in presenting these datasets in context to help guide efficient operations. For example, aerial firefighters wanted to overlay land ownership markers in the space they were active in. Public safety officials wanted to use these maps to note key geological features, such as shifts in altitude. Earth scientists wanted to couple visualizations of tree health from prior field surveys to study changes over time. By updating these visualizations as data became available, analysts could readily compare changes in this data to inform operations and change data collection practices. Further, participants appreciated the ability to visualize the team's locations in the physical environment as a valuable use case for immersive visualizations, providing additional context for immediate comparison between archival data and the current environment.

While the prototype relies heavily on archival and manually collected data, analysts wanted to also fuse this data with data collected by robotic drones and other physical sensors. Our subject mentioned that sensor readings of temperature, wind, and humidity significantly aid analysts in estimating wildfire spread, but that "the more data [they] get, the harder it is to process and analyze and make decisions off of." They noted that the FieldView approach may provide a high degree of transparency in this process, allowing analysts to explore not only archival data, but incoming data streams currently only accessible to operations centers. Further, analysts noted how access to aspects of image data collected by drones may offer increased situational awareness of the overall survey environment. For example, earth scientists noted the ability to compare the canopy from both above the trees and below the trees simultaneously to enrich their analysis. Analysts recommended that fused views should also allow for separating data from different sources, giving field analysts the ability to distinguish preplanning data from data collected from team members and autonomous sensing technologies.

DESIGN ITERATION & USE CASES

Our discussions with domain experts revealed both the utility of the FieldView workflow and specific challenges that FieldView could be extended to address. We revised our FieldView implementation to support a set of three of these use cases (Figure 5). These use cases illustrate novel capabilities of our system tailored directly to the needs of field analysis.

Our initial implementation lacked robust tracking and depth sensing because of our choice to use the Gear VR, limiting our abilities to integrate data into the environment. While these capabilities can be regained through additional sensing devices, many recent headsets have these capabilities readily available. To overcome these limitations, our use cases deploy FieldView using the Microsoft HoloLens. To better address the needs expressed in our interviews unsupported by current approaches, we focus on cases where FieldView must operate off-line due to a lack of connectivity. Case 1 and Case 2 are based on a scenario with multiple analysts collecting simulated scorch rate data. Case 3 explores coordination between humans and autonomous systems collecting aerial and climate data.

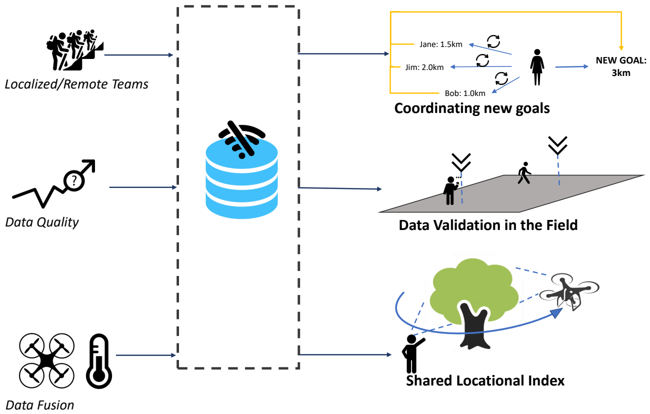


Figure 5. Implemented use cases after our design iteration address localized team coordination, in situ data quality validation, and data fusion from heterogeneous sources, all based on a local datastore.

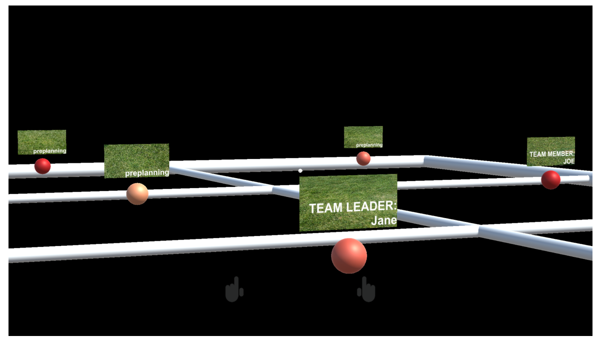
Case 1: Local and Remote Team Coordination

Our collaborators discussed the potential for the real-time data collection and immersive visualization components of FieldView to support better coordination between team members both by aggregating data collected by multiple team members and by enabling a shared situational awareness across multiple sites via image streaming and extensions of the system to VR. While remote fieldsites may complicate use of mobile devices and cloud infrastructures for this approach, our Public Safety and Aerial Firefighting experts mentioned a willingness to carry lightweight portable server devices that could establish a local connection between co-located teams and mentioned experimenting ATAK[1] servers for basic data exchange. We build on this scenario by connecting mobile devices to a local server through FieldView and allowing field analysts to enter and synchronize data to a local team using an offline shared datastore (Figure 6).

To simulate ATAK functionality, we run a Flask server on a Raspberry Pi and connect all analysts to a local network with no Internet connection. Team members are able to add scorch rate samples alongside image references to a local database hosted on the server using the mobile application. Upon entering a new scorch measure, all team members connected to the server have access to the new data. Team members engaged with the mobile platform can quickly view coverage of the intended area on the mobile application's map view, while analysts engaged in immersive analysis can actively view incoming data in context. We anchor our visualization using GPS data from the analysts' mobile device and use the internal depth sensing of the HoloLens to localize data within the field context. Outdoor and large-scale tracking issues of the HoloLens combined with poor granularity in GPS sensing can limit the utility of this approach, but many field analysts leverage more precise GPS devices in practice that can account for these limitations. Within the immersive view, analysts can visualize the scorch rate within that grid area, encoded by a sequential red color scheme on a data point hovering above that area, retaining the visual simplicity identified as critical

[1]http://syzygyintegration.com/atak-android-tactical-assault-kit/

(a) Data coverage map on the mobile device



(b) Contextualized spatial data visualization with team labels

Figure 6. Use Case 1: Team coordinators can quickly determine coverage at-a-glance using a coverage map on a mobile device. Coordinators can survey the distribution of team responsibilities in context to help coordinate data collection efforts based on the resulting spatial distribution.

by all interviewed experts. The immersive visualization allows analysts to select collected data points to toggle a view of past image data collected at that location as well as information about team members who collected data at that location (Fig. 6).

This prototype extends current field analysis capabilities to address three common design considerations identified in our preliminary evaluation. First, this capability gives the local team coordinator the situational awareness to make decisions based on dynamic data. With an updated data model and contextually relevant data situated in the physical environment, field analysts can visualize coverage and synchronize efforts across limited human resources in real time. Second, this implementation highlights the ability to synthesize data collected in the field with data given at preplanning by allowing analysts to update and extend data in existing databases based on mobile inputs. Third, this approach provides greater control over the accessibility of local data, addressing privacy concerns.

Case 2: Data Quality Validation

Experts mentioned the costliness of incomplete and poorly collected data, but said that these lapses in coverage and collection errors are difficult to detect in situ. Automated methods for detecting these errors are limited and current mobile visualizations do not provide sufficient resolution to effectively detect these errors in the field. Further, often understanding the context of collected data can directly enhance expert abili-

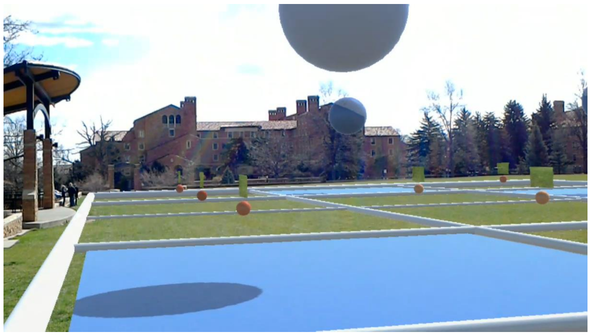


Figure 7. Use Case 2: Visualizations of existing data allow analysts to provide rapid quality checks on existing field data. Scorch data is visualized along a regular grid using small colored sphere to encode scorch rates, mitigating occlusion of the surrounding environment. Blue regions within the grid allow analysts to rapidly identify lapses in data coverage.

ties to rapidly identify and correct for data collection errors. For example, detecting data collection anomalies in situ can call analysts' attention to sensors that may be occluded due to weather or dirt or may be improperly configured. Experts mentioned that detecting and correcting these errors early can lead to substantial savings in both time and budget. By visualizing data in context, field analysts can identify and rectify these errors before returning home from the field site.

Researchers can use the data coverage map on the mobile device to identify regions lacking proper data coverage. Once in that region, they can rapidly identify regions of misssing data using a localized AR overlay (Fig. 7). Areas without collected data are encoded with a divergent blue color to highlight missing data areas, with existing data encoded using colored red points to mitigate environmental occlusion. When the analyst enters data in the mobile application and posts the data to the local server, FieldView removes the missing data visualization and adds the data point in its place.

Similarly FieldView allows analysts to explore patterns across an environment to look for anomalies that might suggest bad or stale data. For example, analysts can survey the scorch rate data across the field and compare the distribution of sphere colors against the expected data distribution and the visible environment to find inconsistencies in the data. Once those inconsistencies are located, analysts can walk directly to any problematic areas, assess the source of the inconsistency, and update data as needed.

This use case addresses the most commonly mentioned design considerations with regard to data quality—data completeness and correctness. Considering these factors in the design of field analysis systems allows analysts to readily bring expertise and contextual information to bear on on-going data collection to identify and remedy simple anomalies. Future extensions of these approaches could integrate automated or comparative solutions into quality analysis. For example, our simulation expert envisioned integrating these approaches with automated processing algorithms used by glacial researchers to call attention to salient irregularities in data. Forest ecologists envisioned direct visualizations of statistical power metrics overlaid on the physical environment to assess anomalies based on data density and multiple measures.

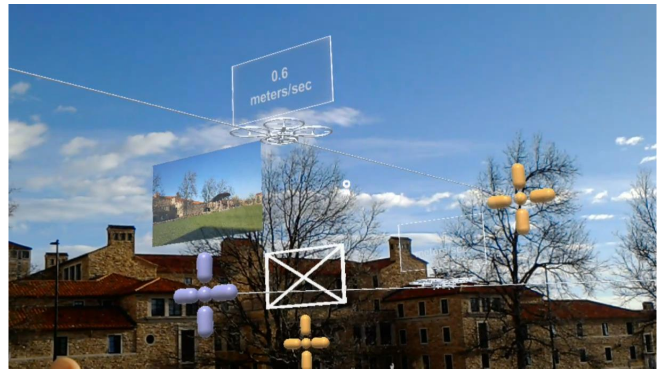


Figure 8. Use Case 3: FieldView can fuse data from field analysts and external sensor streams, increasing situational awareness by providing visual access to multiple perspectives simulateously. We simulate drones flying between waypoints with velocity annotations and path visualizations. Waypoints are encoded orange for uncollected data and blue for collected data, with access to collected image data available on-demand.

Case 3: Data Fusion Across Perspectives

Increasingly, field analysts rely on data collected from multiple sources, including datasets from prior expeditions, data from related sources and sensor inputs from fixed and mobile data platforms. Our discussions with experts revealed the increasing importance of autonomous data collection tools like drones, but noted substantial limitations in their current abilities to fuse ground and aerial data as well as to develop increased situational awareness. While existing mobile solutions allow analysts to view drone footage in real-time, these systems require constant attention and monitoring, inhibiting field analysts' abilities to synthesize information with their own ground context.

Full integration of data from multiple distributed sensors is a complex challenge beyond the scope of this work; however our approach can enable novel interactions with devices in the field and provide more seamless interface between historical data and data actively collected by autonomous sensing devices. To portray this use case, we constructed a simulation of temperature sensors and drones. While our illustrated use case uses data streams from simulated devices, the FieldView architecture is constructed such that these simulated devices are interchangeable with data streams from physical sources.

In this simulation, shown in Figure 8, drones autonomously collect image data along predefined paths between large waypoints defining key data collection objectives and are fused in the datastore using locational indices. Visited and unvisited waypoints are encoded using blue and orange respectively, and clicking the waypoint toggles visibility of image data collected at that waypoint, allowing field analysts to interpret aerial imagery data directly in the ground context. This functionality reflects desires of aerial firefighters and earth scientists to extend their own vision using drones. We augmented virtual drones with information about their current motion and path plan visualization to support colocated operations. The robotic field analyst expressed a desire for increased transparency of drone state through path visualization, which has been shown to enable better collaboration between people and drones [43]. The expanded architecture can also fuse data with inputs from static situated sensors, such as those used in glacial data collection. For example, line graph visualizations can provide realtime transparency into data streams localized using geospatial tags on the static sensors.

While our implementation of human-sensor data fusion as implemented here focuses on interactions with simulated devices, we anticipate that this simulation will serve as a design prompt allowing for deeper investigation into the needs and affordances of data collection across human and autonomous sources in the field, including the design of at-a-glance visualizations for location-aware data. The need for this fusion was a common design consideration across all of the experts we interviewed. Future field analysis systems could explore methods for effectively crafting contextually aware image- and video-based visualizations to efficiently extend situational awareness across multiple team members, including drones, to allow analysts to integrate information into their workflow unobtainable by current methods, such as "being in two places at once" and "seeing through the smoke".

DISCUSSION & LIMITATIONS

We introduce FieldView, a mobile immersive analytics system designed to support data analysis in the field. This system allows field analysts to collect, fuse, and analyze data in context and across teams to bridge spatial and temporal gaps in data collection and analysis. Discussions with ten expert field analysts underscored the potential of these approaches to address current limitations in field practices. Based on these discussions, we extended our current approach to address critical limitations in existing field data collection and analysis practices. Analysts were excited about the possibilities these tools offer and we are in-process of working with experts to tailor and deploy these technologies in their current field practices.

While our work offers insight into how mobile and immersive technologies may support field analysis, there are a number of limitations in our approach that offer interesting opportunities for future research. For example, evolving augmented reality, robotic, and collaborative technologies offer new challenges for effective data visualization, especially in scenarios where data accountability is critical. Immersive AR allows users to utilize their implicit sense of the environment—the trajectory of wildfire smoke or the physical bridge being inspected—alongside relatively sparse, contextualized information. Mobile solutions enable field analysts to engage with complex visualizations in the field, but all interviewees emphasized the need for understanding situational data at a glance. Future research should be done to better understand how field analysis systems can balance the richness offered by both data and context with analysts' need for simple, at-a-glance information.

Our visualizations also focus on fully immersive representations. While these representations allow analysts to quickly engage with contextualized data, the current designs may also occlude the analysts' field of view. Our interviews suggested that visual occlusion is not a significant limitation for envisioned applications of these platforms; however, we were unable to conduct a full field deployment of our system to confirm this hypothesis. Future extensions of this work should more deeply explore the role of occlusion under different scenarios and consider how interaction and context may inform how systems actively adapt to the environment to mitigate potential limitations caused by occluding relevant visual information.

Further, existing hardware has limited tracking capabilities, which limit the precision and resolution of collected spatial data. For example, using commercial devices, we needed to use relatively coarse spatial resolutions to reliably map data to spatial contexts in our use cases. Earth scientists we interviewed mentioned that they did not find mobile phone GPS sufficiently precise for many of their needs. Our current prototype relies on commodity hardware (e.g., mobile phones and commercial headsets), which require substantial integration with external sensing devices to enable more precise data collection methods. At present, analysts must manually adjust input measures to account for potential variations introduced by available hardware. Certain kinds of hardware, such as the HoloLens, are sensitive to other aspects of the environment, such as ambient light. Our current fusion approach relies on cloud-based indexing on spatial locations. However, more sophisticated algorithms can enable rapid fusion of more complex information types. Applications of this approach should actively consider spatial fidelity and other limitations of the deployment platforms as key factors in visualizing field data. Integrating uncertainty into information presentations and developing solutions to account for potential hardware limitations is important future work.

CONCLUSION

Our work continues research in field visualization with domain experts, with an eye toward these nascent technologies. With this work, we presented a prototype to collaborators that conduct field research, conducted a semi-structured interview, evaluated for common themes and iterated on our prototype with a focus on those themes. Future work includes future iterations of the prototype so it suits the needs of field researchers. This research is in a formative stage, but an increased understanding of the pain points and a continued iteration, we can continue work on effective visualization design. While collaborators immediately identified the potential for augmented reality and most already employ drones, it is data visualization that will provide field researchers with the situational awareness they need to conduct their work.

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