INTERNATIONAL JOURNAL OF GEOGRAPHICAL INFORMATION SCIENCE
https://doi.org/10.1080/13658816.2020.1737700

RESEARCH ARTICLE

GeoVisuals: a visual analytics approach to leverage the potential of spatial videos and associated geonarratives

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ABSTRACT

Videos embedded with spatial coordinates, especially when combined with additional expert insights, offer the potential to acquire fine-scale multi-time period contextualized data for a variety of different environments. However, while these geospatial multimedia (GSMM) data include abundant spatiotemporal, semantic and visual information, the means to fully leverage their potential using a suite of visual and interactive analysis techniques and tools has thus far been lacking. In this paper, we address this gap by first identifying the types of tasks required of GSMM data, and then presenting a solution platform. This GeoVisuals system utilizes a visual analysis approach built on semantic data points that can be integrated spatially, which in turn enables management in a unified database with combined spatio-temporal and text querying. A set of visualization functions are integrated in two investigation modes: geo-video analysis and geo-location analysis.

ARTICLE HISTORY
Received 19 August 2019
Accepted 28 February 2020

KEYWORDS
Geospatial videos; geonarratives; visual analytics

1. Introduction

A goal for many spatial scientists, especially those working on social problems at fine geographic scales, is how to acquire contextually appropriate data that better reveal patterns and processes. One interesting approach is to combine location with non-GIS media, such as video (Lewis *et al.* 2011, Kwan 2012b, Ajayakumar 2019, Curtis *et al.* 2019c). Cameras mounted on vehicles (cars, bikes or boats) or carried by hand have been used to capture environmental data covering topics from post-disaster landscapes to infectious disease risk, from homelessness to crime (Curtis and Mills 2011, Curtis and Fagan 2013, Curtis *et al.* 2013a, 2018). These spatial videos can be further enhanced by the addition of audio-narratives captured simultaneously by expert witnesses such as professionals or residents who use environmental cues to contextualize the geographic features or Points of Interest (POIs) (Kwan and Ding 2008, Curtis *et al.* 2013b, Wu *et al.* 2017). These combined spatial videos and geonarratives, here referred to as GeoSpatial Multimedia (GSMM) data, can capture a multi-faceted problem, such as drug use and overdoses, and

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identify key locations and the role they play in the associated landscape. The description of these POIs can create a context which in turn can lead to improved intervention strategies (Rosenstein 2002, Mills *et al.* 2010). The visual and semantic richness of these GSMM data which make this method so attractive also pose software challenges for GIS scientists. Simply put, the combination of location enriched video, along with location commentary containing themes and emotions, and for potentially multiple time periods, exceeds the capabilities of more traditional GIS use. To fully leverage this resource requires new conceptual strategies in how to combine and analyze these different data components. This new software also needs to be flexible enough to allow for non-spatial collaborators to fully appreciate and utilize the method, especially disciplines intrigued by the potential of GSMM but disheartened by the tools currently available to mine its content.

Typically, GSMM contains visual, locational and semantic information with spatio-temporal dimensions. This includes images of POIs, their location and description (context) which are interconnected by the time stamp of the GPS stream. Typical GSMM data collection includes multiple time periods, either different (subject) perspectives or multiple videos to assess temporal change, or both. This can lead to the same location being visualized or described at different times of the same day or across months/seasons or even years. These descriptions also contain a depth that goes beyond the simple meaning of a word. These commentaries may include different geographies of description such as spatially specific mentions, spatially fuzzy (more general descriptions of an area) and spatially inspired (meaning an environmental cue or previous description leads to a more general statement such as the challenges of accessing health care). There is also thematic content, and multiple time frames – not only from when they are recorded but how the description can contain the current, recent, far past or even future insights even in the same comment. Finally, the weight of the statement (for example emotional underpinning) can change the meaning of what is said, or not said.

Given such complexity, and the lack of available software, it is hardly surprising that previous GSMM work has focused on only subsets of the overall data. While there have been a variety of visual analytics (VA) methods and tools developed to work with space-time data (Andrienko *et al.* 2017), these are only suitable when applied to identify locations or vehicle/human trajectories with various visual metaphors and interactions (Crnovrsanin *et al.* 2009, Wang *et al.* 2009, 2013, Gao *et al.* 2012, Tominski *et al.* 2012, von Landesberger *et al.* 2012, Ferreira *et al.* 2013, Kamw *et al.* 2020). VA tools have also been used to explore location-based social media data to discover latent topics and events (Ertl *et al.* 2012, Chae *et al.* 2014, Liccardi *et al.* 2016, Miranda *et al.* 2017). Advances in spatial programming have resulted in bespoke software that addresses certain aspects of GSMM use as the need arises such as GPS correction (Curtis *et al.* 2019b) or spatial narrative investigations (Ajayakumar 2019). It is fair to say, however, that the full capacity of these data is yet to be fully explored. To address this gap, in this paper we present a visual analytics (VA) system that integrates geospatial videos and narratives so that domain researchers and practitioners can more fully leverage this type of resource.

2. Related work

Collecting and analyzing geospatial video data has played a small but intriguing role in the spatial science community over the last decade. For example, Lewis et al.

commented that video is a rich way to capture geography and that offers considerable potential to be a spatial data source (Lewis *et al.* 2011). However, the authors went on to argue that the geographical representation of digital video recording had not fully realized its potential in terms of being an input for spatial analysis and modeling. More recent developments in the technology involved, either a GPS unit and a video camera or one integrated together in the same mobile device, have opened up further research avenues especially in data challenged environments. For example, research using spatial video in hazards and epidemiology has moved from relatively expensive and cumbersome camcorders having coordinates attached to the image as an audio signal generated by a separate device (Curtis *et al.* 2007), to the use of small extreme sport cameras that capture video and GPS simultaneously (Burke *et al.* 2015). Most recently, police body worn cameras are being utilized because of their robustness, and quality of GPS, video and audio recording (Curtis *et al.* 2019d). What has lagged behind these technological improvements has been the associated software, so in effect Lewis and colleague's comments still hold.

Environment inspired interviews have also begun to gain traction with geographers (Kwan and Ding 2008, Evans and Jones 2011, Mennis *et al.* 2013) as a way to add context into finer scale spatial studies. The basic concept is that a subject is inspired by his/her environment and the capture of that narration, when linked to a simultaneously recording GPS unit, offers the opportunity for context enriched spatial data creation. Previously 'go along' interviews had been used to consider activity spaces (Bell *et al.* 2015, 2017), the link between health and place (Carpiano 2009), aging (Lager *et al.* 2013), and mobility challenges for those with disabilities (Butler and Derrett 2014), but real advance came with the simultaneous addition of geography with geonarratives (Kwan and Ding 2008) where coordinates are linked to the interview. This offers the opportunity to spatially and socially capture problems in a dynamic multi-temporal way (Kwan 2013). In this way, the description on a path through the landscape being studied can reveal spatially specific insights, for example about safety and activity Mennis2013, or planning and place attachment (Jones *et al.* 2008, Evans and Jones 2011, Bergeron *et al.* 2014).

A subset of these geonarratives are spatial video geonarratives (SVG), where the visual richness of the video image is combined with a spatialized go-along interview, with all data streams being synced to a GPS time stamp. This allows the researcher to use a series of iterative investigations that move between media, location, comment, and across multiple time periods. Each informs the other in a series of research loops; what is said, where is it said, what can be seen, what did others say, does this match with a previous comment, location or image and can a connection between all these data types be found elsewhere? The limiting problem is that to achieve this type of complex inquiry requires bespoke software. For example, recent improvements in a GIS allow for a video to be viewed, but offer little else than having it as a simple digitizing source. The addition of commentary (narratives) further complicates the issue as there is little opportunity within the GIS to mine these data types for themes, textual patterns or sentiment. GSMM data pose a further challenge in terms of temporality. At the simplest level, different videos can be collected on different days/weeks/years to offer multiple perspectives on the same space across time. But time is often fluid within the narratives with a description including the past (far and recent) and the present even in the same sentence (Curtis *et al.* 2019c).

3. A visual analytics framework for geospatial multimedia data

3.1. Overview

To bridge this gap to visualizing and analyzing complex space-time-social interactions we initially developed a conceptual frame based on what are the likely and future tasks required by domain users. To address the described current research deficiencies, we focused on both geospatial video-based and location (street and region)-based tasks, supported by semantic and sentiment analysis to allow for cross-site (and time period) comparisons. To achieve this, a specific space-time object that integrates and harnesses multi-type data elements over space is required. To solve this, we used the geo-atoms (Goodchild *et al.* 2007) of GSMM data to build a VA structure called Semantic Data Points (SDPs). The VA structure enables both video- and location-based analyses, and a spatial database could be designed to accelerate data retrieval in order to visualize video clips, pictures, and narratives through the use of spatial and temporal constraints. In addition, semantic visual queries could be enabled by a text search engine braided together with the spatial indexing. The richness of themes within the narratives could evolve iteratively through a co-occurring keyword search based on associate rule mining in the narratives. Adding further insight would be a sentiment analysis tool utilizing natural language processing (NLP) to reveal emotional subtext (and therefore further context) in the descriptive statements.

The GeoVisuals platform has been built on this concept to interactively manage, visualize, and analyze GSMM data using a rich set of visualization widgets and interaction functions developed for geospatial, semantic, sentimental and comparative studies, with a Web-based interface consisting of multiple coordinated views. Map views can be explored (and compared) by integrating map canvas with a set of semantic and image visualizations including top keywords buckets, sentiment timelines, video player, keyword filters, word tree, and spatial correlation view. Google StreetView is also incorporated so that users can compare their own data collections with Google data (in effect extending the time frame of comparative imagery). GeoVisuals is shared at a website, as an open-source software under BSD license.

GeoVisuals was also developed in constant consultation with researchers working with GSMM data so that the most useful tasks, both currently available or hoped for, could be included. In return, this resulted in a constant feedback from the researchers, and access to real project data. Case studies were acquired from multiple cities in the United States (and though not reported here, from various international settings) and these provided a rich test data set often extending across multiple time periods. The case studies included health investigations, disaster and built environment assessments, while narrative subjects included professionals and residents. While example data are presented in this project it should be noted that for the figures we have changed text, maps and images to follow privacy protection and ethical policies associated with the original IRB (Institutional Review Board). While the examples remain real, they are a mixture from different case studies merged for illustrative purposes only.

3.2. Typical domain tasks

The authors have been involved in multiple SVG collaborations with topics including homelessness, violence, drug use, and internationally, cholera and other enteric disease risk, mosquito vectored diseases, and access to clean water (Curtis *et al.* 2016, 2017, 2018, 2019b, 2019c, 2019d, Krystosik *et al.* 2017, Smiley *et al.* 2017, Ajayakumar *et al.* 2019). From these projects common tasks have emerged that are frequently required to both solve the problem at hand, and to serve the needs of local collaborators. For example, for their work in Cambodia (Tyner *et al.* 2018, Curtis *et al.* 2019a) which investigated the forced evacuation of the populace from Phnom Penh, the research team needed to be able to see the map of SVG routes, images from the video and associated descriptions by the evacuees. As multiple narratives had been collected one task was to see how descriptions varied for the same location. Initial mining of the narratives using the keyword 'violence' revealed associations such as 'solider', but also co-occurring words such as 'bridge'. By combining these research threads together, it was possible to determine that the bridges acted as choke points where the streams of people converged. This in turn led to increased violence, especially as the length of time the people had been walking (approximately three days) also meant these choke points occurred when sickness and exhaustion were at their peak. This is typical of the way these data are used. While any project can be different and require specific tasks, the following set of tasks are most commonly needed or desired.

(I) **Basic GSMM Browsing**:

(1) **Video Browsing**: To be able to watch a spatial video with associated and supporting information, such as what is being said along the path.
(2) **Location Drill-Down**: To be able to drill-down at any point on the path to see a still image and what is being said about that location, for example for a particular POI.

Both 1 and 2 are integral to effective GSMM data use and can be achieved through other off-the-shelf software or basic spatial programming.

(3) **Temporal Comparison**: To compare the semantic and visual information at the same place for temporal GSMM data (e.g. have changes occurred at this location between video runs?).
(4) **Semantic Mining**: To find and study important locations in a trip identified in the narrative (e.g. where are the locations when "drug" and "burglary" are mentioned by the narrators?).
(5) **Visual Content Mining**: To find important locations from the video imagery (e.g., where are blighted houses) by automatic object/scene detection.

(II) **Geo-location-Based Analysis**: More complicated still are the analytical demands over geolocations:

(1) **Keyword/Theme-Based Searching**: To extract out different geographies (streets, regions, etc.) by mining the descriptions contained within, such as through the selection of keywords or themes. For example, which streets have high drug activities together with burglaries?

(2) **Geonarrative Sentiment Analysis**: To identify locations of interest by mining inherent sentiments of narrators. For example, which locations are discussed in highly negative/positive terms?
(3) **Video Content Browsing**: To observe the geographical distribution of specific video contents, such as visualizing a map of blighted houses in a city automatically from the video.
(4) **Location Comparison**: To compare narratives, keywords and themes at different streets/regions, or to compare various perceptions and emotions about places.

Currently, GeoVisuals system is designed for major user tasks except I.5 and II.3, which will require further developments in computer vision and AI techniques.

3.3. SDP structure and visual analytics scheme

A common need identified in the previous section was how to find and analyze critical locations based on their visual appearance and spatial semantics. The semantic information from the geonarratives includes descriptions, opinions, related events, and evaluations of spatial locations such as shops, houses, buildings, streets and regions. We define the geographical locations associated with semantic narratives and visual views as *semantic data points* (SDPs). By joining semantic and visual information and GPS trajectories in spatiotemporal space, it is possible to:

- Perform both location-based and trajectory-based analyses singularly or in combination;
- Process the massive, hybrid data with SDPs as the basic units, and then store them in a unified spatial multimedia database;
- Facilitate spatial aggregation and study of semantics and sentiments based on trips, streets and regions;
- Enable the comparison study of multiple datasets intersecting at important locations.

In addition to its GPS location, each SDP can be considered as a data unit to store: (1) the corresponding video frame, (2) the video timestamp, (3) the sentences (and keywords) extracted from narratives about this location, (4) the recording time, (5) the street segment on which the point is located, (6) the point's corresponding region (e.g. zip code). New data can also be created by selecting a GPS point, labeling it as SDP, and then adding comments.

As shown in Figure 1, a visual analytics scheme built up on SDPs facilitates a visual analysis based on trip trajectories, streets, or regions, allowing for tasks in Section. 3.2 to be easily addressed as the videos and images, semantic information, and narrator sentiments are visualized together on the map. In summary, SDPs play an important role to bridge the gap between the heterogeneity and complexity of data and the ease of visual exploration.

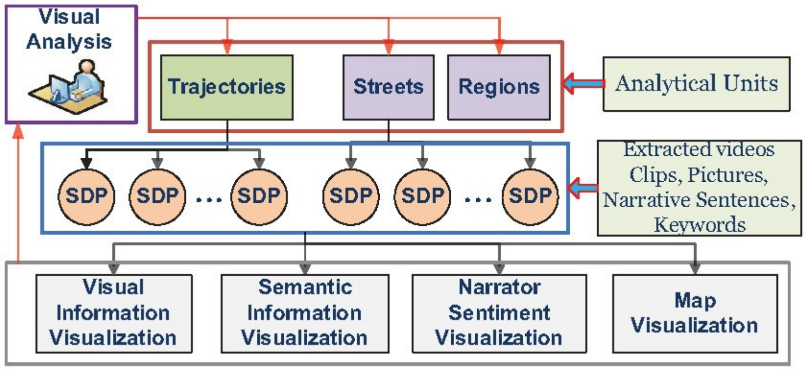

Figure 1. The visual analytics scheme built up on Semantic Data Points (SDPs) allowing for investigations using trip trajectories or different geometries (streets or regions).

4. Geospatial multimedia data management

4.1. Data flow

The data flow of GeoVisuals is illustrated in Figure 2. First, raw GSMM data are processed to prepare the keywords, sentences, sentiments, images, and videos, which are registered with SDPs. Then, the SDPs are matched to geographical street and regions. These data are stored and managed in a spatial database with geo-spatial indexing, which is combined with a text search engine to enable fast keyword filtering and data retrieval. GeoVisuals accesses these data through spatio-temporal queries, sentiment and semantic queries, as well as trip trajectory queries to support interactive visual analysis.

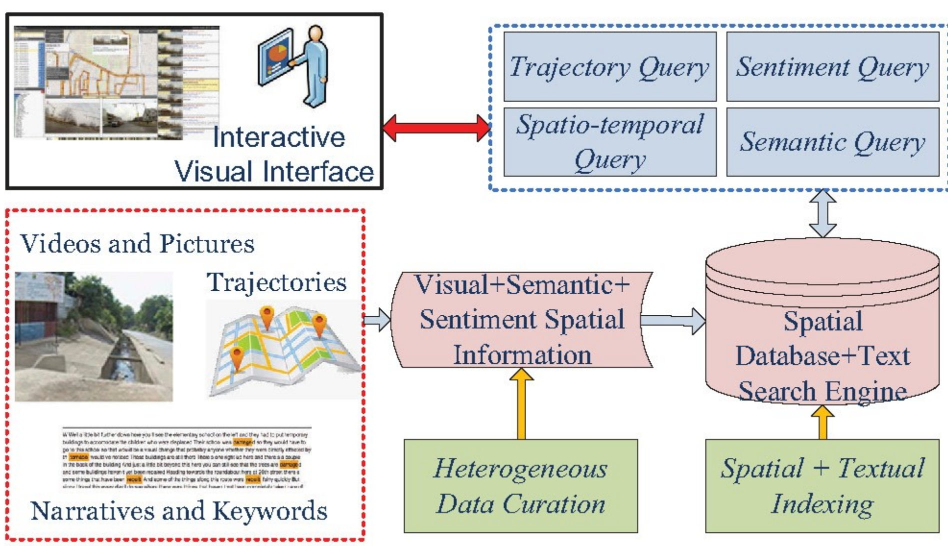

Figure 2. GeoVisuals data flow overview. Heterogeneous data are processed to extract visual, semantic and sentiment information, which are stored in a spatial database. This allows for various interactive visual analytics supported by a set of data queries over the database.

4.2. Data processing

Each spatial video is associated with a trajectory consisting of a stream of GPS points all of which have time stamps. The trajectories are processed as follows.

4.2.1. Textual narrative extraction

The audio narration is extracted from the raw video and then converted to text. This can be completed either by human or by manual editing after automatical transcription with Google's Cloud Speech-to-Text tool. For many GSMM datasets, automatic audio transcription is problematic due to excessive background noise, variations in the language and accent of the subject, and topic-specific terminology. For the case study data used here, and for most SVG projects, transcriptions are completed manually. The video and transcription then have their visual and semantic contents registered to SDPs.

4.2.2. SDP-based data registration

First, for each trajectory, we extract all the SDPs from the original series of GPS points. The SDPs are those GPS locations (with corresponding time stamps) where a comment is made by the subject. These comments are then associated with these SDPs. Second, each SDP is linked to the visual data by storing the time stamp of the corresponding video at its location. When accessed the corresponding video clip at this SDP location can be immediately played. Third, each SDP stores the images of its location, which are extracted from the keyframes of the video. While SVG data can be collected using different transport modes, such as by car, on a bike, on a boat or by walking, here cameras were mounted on the left and right side of an automobile, and the synced images from both sides have been extracted.

4.2.3. Semantic keywords extraction

For each SDP, its geonarrative content is processed (by a natural language processing toolkit) to remove stop word (such as 'the', 'a', 'an', 'in'), merge word tenses (such as 'had', 'have', 'having'), and then extract a set of useful keywords. These keywords are given weights to form a semantic vector. A keyword's weight can be proportional to its appearance frequency in all geonarratives (i.e., Term-Frequency method). In addition, the weight can also be defined by the Term Frequency-Inverse Document Frequency (TF-IDF) method, which is typically used in text data mining (Kao and Poteet 2007). In TF-IDF, a high weight means that a keyword appears frequently in the corresponding SDP narrative, but it is not a common word appearing frequently in all SDPs.

4.2.4. Sentiment scores computation

Sentiment analysis in natural language processing can identify whether the expressed opinion in a document or a sentence is positive, negative, or neutral. This can be helpful for analysts to study the SVGs since the emotion and opinion of narrators play an important role in understanding how the landscapes are contextualized. Therefore, a sentiment analysis tool (NPM 2019) is utilized where each word is rated as an integer between minus five (negative) and plus five (positive) (Nielsen 2011). Each SDP is given a sentiment score by summing up the sentiment integers of all the words in its narrative sentences.

4.2.5. SDP map matching and information aggregation

SDPs have longitude and latitude coordinates. But they do not include which streets and regions the SDPs intersect. To enable street/region-based analysis, these SDPs are matched to the street network geometry from OpenStreetMap. In particular, the geographical bounding box of all the trajectories being studied is calculated. The geometry of all street segments, the names and the POIs inside this box is downloaded and processed. Next, a map-matching algorithm is applied to project the SDPs to street segments. Similarly, given geographical regions of interest, the SDPs can be matched to them as well.

After map matching, semantic and sentiment information is aggregated over the streets or regions for visual exploration. The top keywords of a street (or region) are computed from the weights of all the keywords of the SDPs intersecting this street (or region). Meanwhile, the sentiment scores of these SDPs are accumulated to compute a street (or region's) sentiment score by averaging the scores of all keywords.

4.3. Spatial database of GSMM data

4.3.1. Data organization

A spatial multimedia database is devised to support data queries for interactive visualization. Specifically designed for the GSMM data, instead of using a traditional relational database, each SDP is stored as a 'document' in a NoSQL database (MongoDB is used in the implementation). An SDP document encapsulates the location, time stamp, and links to the corresponding video file and video time, narrative sentences and keywords, as well as the street segment and name it belongs to. The document also includes a trajectory (trip) ID to link this SDP to the trip. This SDP-based scheme has good extensibility when other types of data are incorporated such as demographic data, geo-tagged social media data, etc. The database also stores geo-structures of street networks and region geometries.

4.3.2. Spatial and text indexing and queries

Spatial indexing is constructed over spatial objects in the database to facilitate fast data retrieval of street segments and regions. The spatial indexing algorithm is based on a B-tree subdivision of the space and then a geohash string is used to quantify the location of one SDP to a cell in the tree (Fox *et al.* 2013). In this way, the spatial indexing scheme can quickly retrieve those SDPs inside any queried region.

A text search engine is integrated with the spatial database to search for and find SDPs whose narrative sentences contain identified keywords. In this way it is possible to conduct flexible and joint queries by wildcard, Boolean, and fuzzy conditions, allowing for interwoven spatio-temporal and semantic queries.

5. Visual analytics with GeoVisuals system

5.1. System overview

To fulfill the typical set of VA tasks of GSMM data suggested by domain users (Section 3.2), GeoVisuals supports two investigation modes: Trip Mode which focuses on the path and Spatial Mode for street/region investigations.

5.1.1. Trip mode visual interface

As shown in Figure 3, the Trip Mode interface consists of several parts: (A) Trip list that shows the video recording trips at different times; (B) Map view that displays trip trajectories and SDP points on them. The SDPs can be shown as markers or as a heatmap; (C) Thumbnail view that shows details of the SDPs on a trip; (D) Video view that plays and controls the videos with semantic hints; (E) Semantic filter that uses keywords to select SDPs and associated trips.

5.1.2. Spatial mode visual interface

In Spatial Mode, three different analytical methods can be applied (Figure 4(g)): Semantic Study, Sentiment Study and Keyword Tree Study. Users can also set spatial analysis units as street segments or by regions that are partitions (for example by rectangle or hexagon) of the urban space, the importance of which will be explained in Section 5.3.2. In Figure 4, for example, sentiment Study and streets are selected. The interface consists of: (A) Street List that shows ranked list of streets by SDP counts; (B) Map View that color codes streets according to their sentiment scores; (C) Sentiment Panel where streets can be selected for different time periods to further investigate their associated sentiment; (D) Detail View then displays image and narratives for selected streets; (E) Timeline View of time-varying sentiment scores; (F) Keyword Filter for interactive study.

Figure 3. GeoVisuals Interface in Trip Mode. (a) Trip list displays trips at different times in which spatial videos and narratives are recorded. The total numbers of Semantic Data Points (SDPs) and top keywords are shown. (b) Map view plots trip trajectories (blue). A selected trip (Trip 4) is highlighted in orange. The SDPs are shown in green which are selected by keyword filter. Several optional insets show supplemental information. The SDP acts as a map entry point for both snapshot images and narrative details at that location. (c) Thumbnail view shows the visual and semantic information of all SDPs on the selected trip. (d) Video view plays the trip video with visual hints of the SDPs and top keywords. (e) Keyword Filter allows users to query SDPs with a Boolean condition in this example 'campus OR school'. These maps, associated images and text have been manipulated from real examples in other locations and grafted into this figure for illustrative purposes only.

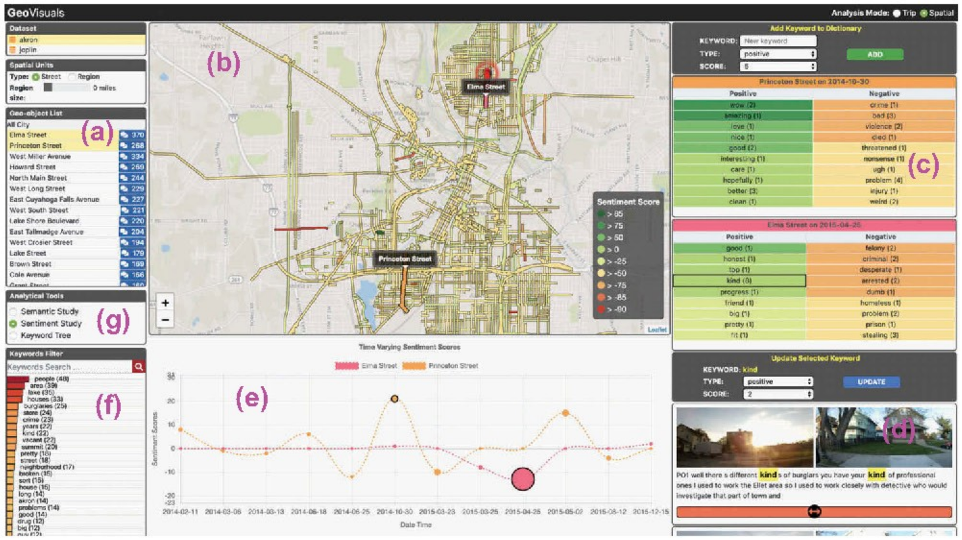

Figure 4. GeoVisuals Interface in Spatial Mode for sentiment study. Three analytical tools are available: (g) Semantic Study, Sentiment Study and Keyword Tree Study. Spatial units cab be set as streets or regions (rectangle or hexagon). Here Sentiment Study is selected and streets are used as analysis units. (a) Street List shows streets ranked by the number of SDPs. (b) Map View displays streets color coded by their sentiment scores. (c) Sentiment Detail View shows important keywords on selected streets at different times. (d) Detail view of visual information and narratives. (e) Timeline Charts of varying sentiment scores of selected streets. (f) Keyword Filter. These maps, associated images and text have been manipulated from real examples in other locations and grafted into this figure for illustrative purposes only.

The different views are coordinated together allowing for a variety of exploratory approaches, with the results from one panel or figure guiding the selection or changes in another.

5.2. Trip mode: videos-based analysis

For Tasks I.1-I.4, a set of visualization tools are designed to help investigate the spatial videos, trajectories, SDPs, and their relationships.

5.2.1. Overview example

We refer back to Figure 3 for a more detailed explanation. Any of the trips (identified by date of collection) in Figure 3(a) (Task I.1) can be selected, which initiates the video play here showing the left and right view (though just one side can be selected). A bright green dot progresses along the route synced to the video (Figure 3(b)). A sense of what is being said at the locations being passed is displayed as frequently occurring keywords on the slider bar. A navigation inset (on the left of Figure 3(b)) shows a more detailed view of where the video image is, which is useful if the main window is displayed at a more coarse scale. Below this inset, an optional text box shows the changing narrative for each SDP along the route. This same text is displayed in the highlighted box of Figure 3(c), the image also corresponding to the main video view. The images before and after, and the corresponding text that satisfies the keyword search (Task I.4) in Figure 3(e), in this case campus or school, are displayed for additional context (the corresponding locations are smaller orange dots on the map).

Adding and editing SDPs: in consultation with SVG researchers, it was found that it would be useful to add SDPs to the media. In this way either enriching an exploratory analysis with notations or adding the insights of a third party could be achieved. To do this an SDP can be created by clicking any point on the map which has no narrative and adding a description. This point then turns to an SDP. For example, if the researcher is interested in mapping graffiti, including a contextual interpretation of these, locations would be marked by watching the video and adding an SDP with a description. It is also possible to edit or delete the existing SDPs.

5.2.2. Comparative study and spatial correlation

One powerful use of GSMM data is to see how change has occurred at the same location over time (Task I.3). This can be achieved in GeoVisuals through any SDP or another point along a route on the map. Figure 5 provides an illustration where all images at a location (within a tolerance buffer) are displayed, along with any accompanying narrative. Google StreetView at this location (and its date of collection) is also displayed for a further time period of comparison. In Figure 5 the tall red sign is visible in the left side views and the top Google StreetView window. These comparative views can be used to see how quickly recovery is occurring along a route in a post-disaster environment or how a blighted city block changes across a year.

An additional way to guide this comparative process uses a spatial relation analysis of the video trips (Figure 6). When the current trip travels to a point P, other trips are shown as equalizer bars. A long bar indicates a trip is closer in distance to P, which may mean this is a trip that should be compared to assess change. The distance is calculated by the closest point on each other trip to P, so the bars change as the spatial video progresses. It is possible to switch to any of these other trips using these distance bars as a guide.

5.3. Spatial mode: street/region-based analysis

5.3.1. Sentiment study

Sentiment analysis can also be applied to the narratives in order to reveal underlying nuances or 'feelings' (Task II.2). For example, in Figure 4(b), streets are colored by their semantic scores which can then act as a selection guide using either the map or the list view (Figure 4(a)). A timeline view (Figure 4(e)) displays time-varying sentiment scores with more negative mentions falling below the line, and positive above. Using the bubbles as a guide, the corresponding sentiment list is displayed (Figure 4(c)) with top positive mentions in green and negative in orange. Hue intensity displays the strength of the mention, from −5 to 5 (Nielsen 2011), while the number is its frequency of mentions. Validations are also possible as while the sentiment analyses can suggest the 'emotional' perception about the street, clicking on a selected word shows the location and context to validate or question the finding (Figure 4(d)). In the displayed example kind is a figure of speech rather than a positive expression. To counter such errors, domain-specific sentiment adjustments are possible. The score of any keyword can be

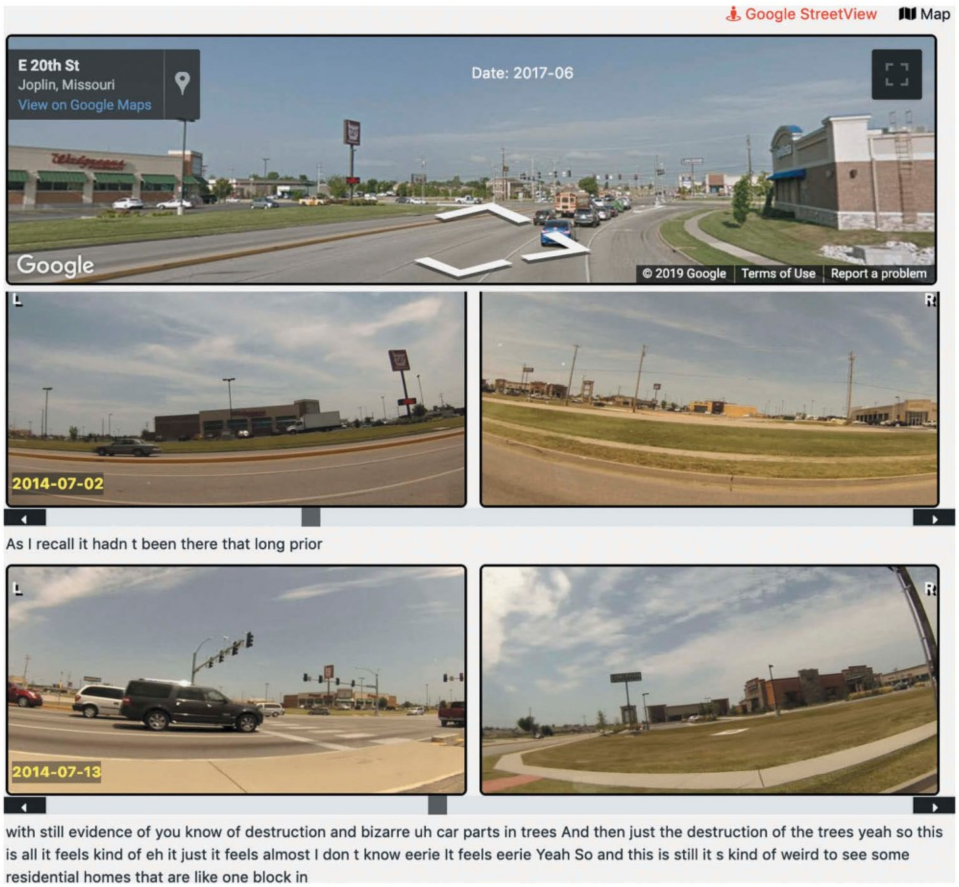

Figure 5. Comparative study of visual and semantic information at any location from multiple videos and Google StreetView. The slider bar allows movement anywhere along the route.

changed (given more or less weight) or even removed. New words which have domain-specific meaning can also be added and the sentiment lists and timelines are updated accordingly.

5.3.2. Semantic analysis of streets and regions

Semantic comparisons can also be made across different geographies (Task II. 4), including by streets, square cells or hexagon cells as shown in (Figure 7(b)). Selecting one of these geographies on the map, which results in the border being highlighted in black, allows for further investigation of the emotional mentions occurring inside. These selections are seen in (Figure 7(c)), which displays the top keywords for each selected geography. The color coding displays the frequency of times that word is mentioned in that geography. In Figure 7 the word house is most frequently mentioned in Region 1. It is possible to drill down to select multiple keywords with AND/OR operations (Figure 7(c)) and find where these mentions occur on the map along with the related SDPs. A gallery view by keywords (top left corner of Figure 7(b)) can be expanded to visualize all SDP pictures and semantics (not shown here to save space).

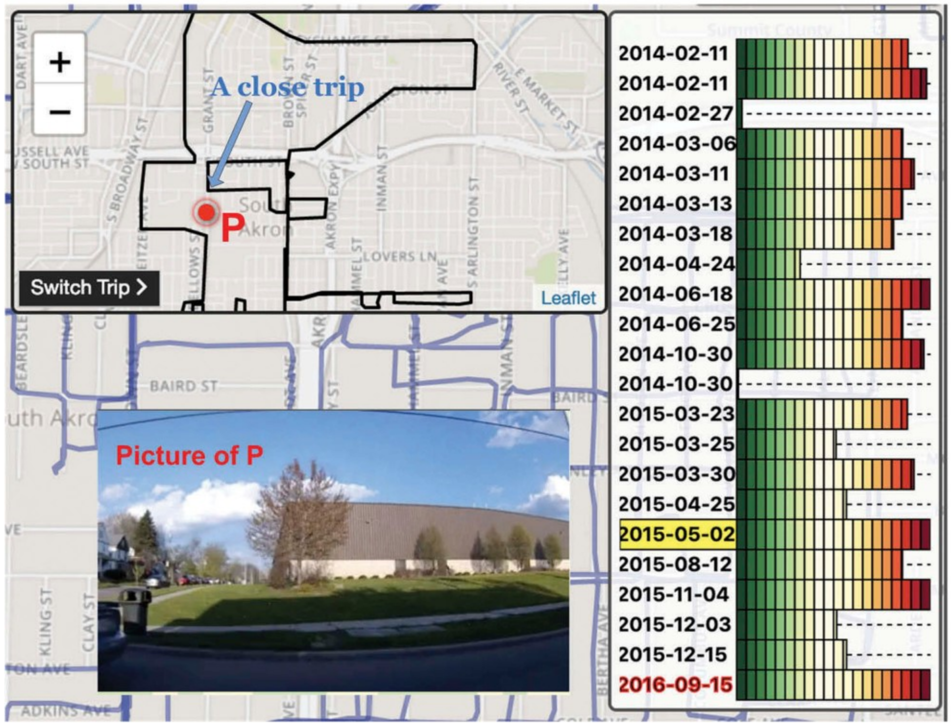

Figure 6. Spatial relation study: this allows for a proximate trip to be accessed for across data collection time periods.

For example, in Figure 7(b) four different regions are selected. Three of these areas have mentions of 'drug' and 'meth' (Methamphetamine) referring to illegal substances in the bubble view. By adding a further search term 'drug AND vacant', the specific SDPs are revealed in these regions. Accessing one of these SDP points shows a narrative describes a vacant apartment where overdoses have occurred. For the researchers, this could be the site for further investigation or intervention.

5.3.3. *Studying keyword relationships*

A visual semantic study (Task II.1) can also be applied through the use of a word tree (Wattenberg and Viégas 2008), which searches for associated context around a keyword. To do this, frequent term sets from all the narrative documents are discovered by the apriori algorithm in association rule mining (Agrawal and Srikant 1994). Figure 8(a) shows the word tree where the root layer (on the left) displays top keywords for a selected street or region. The branches from a keyword, such as tornado, are displayed with all other keywords that occur in the same SDPs as containing 'Tornado'. These are ranked and the top ones displayed as a child layer. The circle size indicates the number of SDPs having the word. In each layer, keywords are ordered from top to bottom by their frequency. A selection of any combination of keywords can be displayed as maps, thumbnail images and the associated text. This facilitates both comparisons between regions and the ability to learn between the different media types (Task II.1 and II.4).

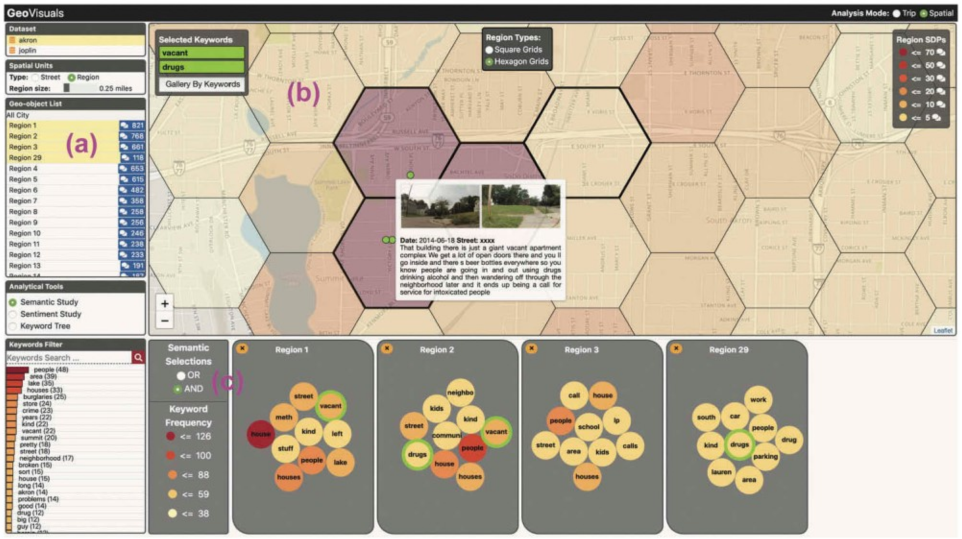

Figure 7. Semantic study interface in Spatial Mode. (a) Users select regions of interest; (b) Map View with selected regions highlighted by black borders; (c) Bubble Buckets display top keywords in the selected regions. Users can compare these regions and select multiple keywords to find SDPs including them. As previously mentioned, these map details have been manufactured with real examples being grafted in from other locations.

6. Conclusion and discussion

Spatial video (SV) and especially spatial video geonarratives (SVG) or here as we refer to them as geospatial multimedia (GSMM) offer exciting opportunities for fine-scale spatial research. The visual richness of a video, when merged with an associated coordinate, allows for previously unmapped areas to be captured for single or multiple time periods. Indeed, this approach has already benefitted researchers in ephemeral or challenging environments both in the United States or overseas (Lue *et al.* 2014, Krystosik *et al.* 2017). But this opportunity goes beyond simply adding spatial data to fill in gaps, with the addition of a narrative these data become contextualized (Curtis *et al.* 2018), thus achieving a current research goal for many in GIScience (Kwan 2012a, 2012b). GSMM opens fresh avenues for spatial research in terms of how we work in human spatial units (Jaskot *et al.* 2014). For example, a typical GSMM contains three different media types – video, geocodes, and text. In this paper, we have linked these together (using the time stamp of the GPS stream) as an SDP-based data model. An image on the video (for example a gang graffiti) might stimulate a line of inquiry, for example can similar markings been found (seen and mapped) at other (SDP) locations? If so, how do the comments made about each location vary? Using the idea of a deep or thick map (Presner *et al.* 2014, Harris 2016), what else is revealed from personal experience (maybe post-traumatic stress from previous violence exposure) or broader impacts on the community, by drilling down into the SDP? Adding further GSMM data capturing other perspectives or time periods can be accessed in the same way. Now we can make contextualized comparisons across both space and time. We might find the impact of an encroaching second gang, which has further consequences as to how the community utilizes certain open spaces. From these

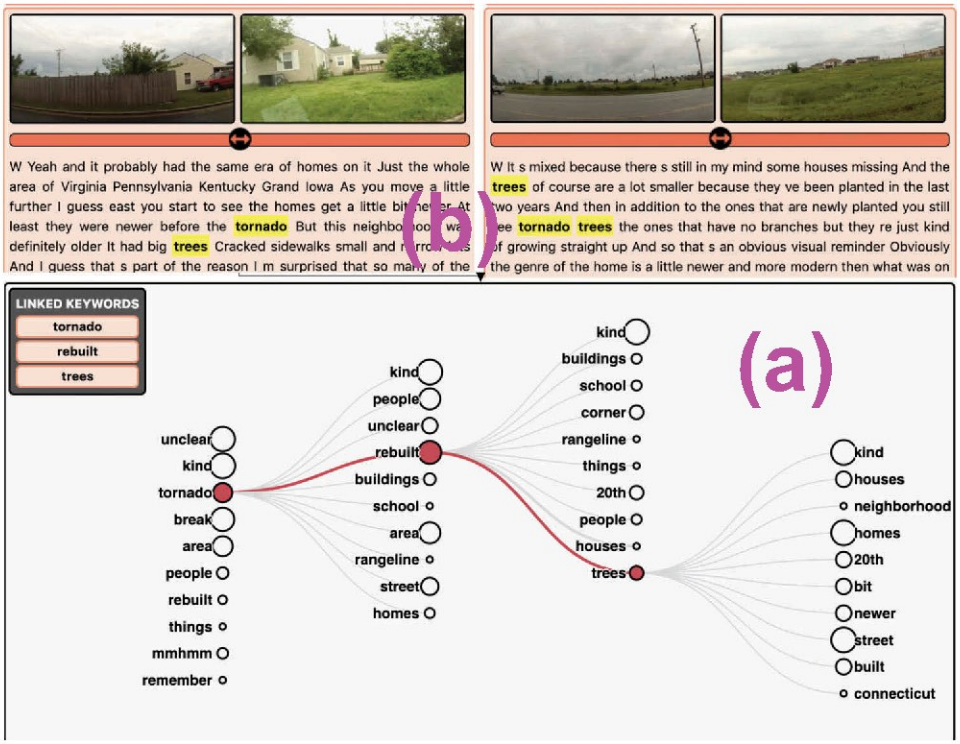

Figure 8. Interactive keyword tree for studying keyword relationships. (a) Users can browse and select highly co-occurred keywords in different layers. (b) Detail view of two corresponding SDPs.

contextualized spatial insights we can start to understand emotional landscapes, especially regarding fear. While this description of a research strategy is intuitive, working with such complex spatially linked media, where themes, emotions, and images inform each other is virtually impossible in a traditional GIS environment (Knowles *et al.* 2015).

Previous SVG work has been reliant on bespoke code SVG media, such as how to map the various themes associated with the SVG (Ajayakumar *et al.* 2019). In this paper, we have made a large advance in being able to more fully leverage these kind of data. Our conceptual frame allows for comparison of multiple trips, using a combination of inter-spatial connection between trips and contextual similarity, to see how places change both visually and in perception. Even more than this, the sentiment of these spaces can also be compared. Various visual tools, utilizing dynamic graphics and maps allow for these data to be explored interactively, and iteratively. In this way the research previously described for Cambodia is more easily facilitated as we can see how many evacuation narratives intersect with this one choke point, and then read what the subjects said about that location.

This is only the first step. GeoVisuals has begun the dialogue in terms of what can be achieved here. All of the components described here can be improved, expanded and tailored to different research settings. Currently, data upload is cumbersome, but future streamlined stand along and web-based versions would support more ubiquitous use. While textual exploration is possible through keyword searches, and finding co-occurring terms through keyword trees, and even identifying emotional content, future work could more effectively mine narratives for themes and automatically detect objects from videos, which could be further categorized into temporal bins. SVG data are far richer in content than the typical social media data used for sentiment analysis, so the rather crude explorations displayed here could lead to not only advances in how we display emotion but also in the nuances of spatialized sentiment – how do we identify on the landscape what is being discussed from an emotional perspective, and how do we capture the way emotion is conveyed in the voice and not just the transcribed word?

Finally, collecting SVG data raises various confidentiality and ethical considerations. We still struggle with more traditional issues of spatial data confidentiality, especially regarding cartographic representation and data sharing (Boulos *et al.* 2009), yet GSMM adds even more challenges. SVG data collection typically requires IRB approval. Products from these data, especially graphics with facial images and original voices should be masked for public dissemination. Indeed, the graphics that appear in this paper have had aspects (descriptions, images, maps) randomly changed. However, for this type of work, there is still the potential for unintended consequences. The negative descriptions of a neighborhood, or even a store, may cause harm to those who reside or own the buildings in question. It is also possible that descriptions may contain personal information that can be attributed to a resident even if he/she is not seen. While GeoVisuals offers the opportunity for more insightful research, which in turn should help stimulate more data collection, there is need for simultaneous studies on these potentially harmful consequences.

Acknowledgments

The authors would like to thank the anonymous reviewers. We also appreciate the contribution of Eric Jefferis, Susanne Mitchell, Lauren Porter, Steve Smith and Jayakrishnan Ajayakumar for their work on the original data collection.

Data and code availability statement

Spatial video geonarrative data mentioned in this paper are collected under strict Institutional Review Board supervision. The original clearance states that neither the original video (because it contains a subject's voice) or the complete narrative of that subject's interview will be made available to anyone other than the research team. The software package is available on figshare, accessible via 10.6084/m9.figshare.11629095. All the data used in this package are synthetic. While actual narratives were consulted to provide a 'real-world experience', the actual text, and corresponding locations have been created. Therefore, the pattern, association, or any meaning gleaned from data supplied with this software are not 'real'.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported in part by the U.S. NSF under Grant 1535031, Grant 1535081, and Grant 1739491. Andrew Curtis is also supported by the National Institute of Justice award [2013-R2-CX

-0004]. Xinyue Ye is also supported by NJIT FSG FY20 Faculty Seed Grant Award and NSF OIA-1937908.

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