Mirante: A visualization tool for analyzing urban crimes

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***Abstract*—Visualization assisted crime analysis tools used by public security agencies are usually designed to explore large urban areas, relying on grid-based heatmaps to reveal spatial crime distribution in whole districts, regions, and neighborhoods. Therefore, those tools can hardly identify micro-scale patterns closely related to crime opportunity, whose understanding is fundamental to the planning of preventive actions. Enabling a combined analysis of spatial patterns and their evolution over time is another challenge faced by most crime analysis tools. In this paper, we present *Mirante*, a crime mapping visualization system that allows spatiotemporal analysis of crime patterns in a street-level scale. In contrast to conventional tools, Mirante builds upon street-level heatmaps and other visualization resources that enable spatial and temporal pattern analysis, uncovering fine-scale crime hotspots, seasonality, and dynamics over time. Mirante has been developed in close collaboration with domain experts, following rigid requirements as scalability and versatile to be implemented in large and medium-sized cities. We demonstrate the usefulness of Mirante throughout case studies run by domain experts using real data sets from cities with different characteristics. With the help of Mirante, the experts were capable of diagnosing how crime evolves in specific regions of the cities while still being able to raise hypotheses about why certain types of crime show up.**

I. Introduction

Understanding crime patterns in urban areas is a challenging problem due to the interplay between the spatial and temporal dynamics of crimes, the great variability of patterns among the different types of crimes, and the large amount of data involved in such analysis. In this context, the branch of Geographic Information Systems (GIS) called *Crime Mapping* focuses on developing tools to explore and analyze the spatio-temporal behavior of crimes, leveraging the importance of local urban, social, and environmental characteristics as determinants for crime opportunity [1], [2]. Current crime mapping tools combine techniques from different fields such as mathematics and statistics [3]–[5], machine learning [6], [7], optimization and visualization [8]–[10], and social sciences [11], [12]. Examples of crime mapping systems implemented to increase transparency for the population and to support agencies in charge of public security are *LexisNexis*[1], *NYC Crime Map*[2], *CitizenRIMS*[3], and *CrimeMapping*[4].

An important aspect of crime mapping is the spatial discretization. Most techniques rely on regular grids with crime data aggregated on grid cells, each covering hundreds of square meters. However, recent studies point out the importance of analyzing micro places [13]–[16], as crime rarely concentrates on regions larger than a street segment or corner. In fact, several researchers have shown that crimes mostly occur near specific locations such as bars, fast-food restaurants, check-cashing centers, and pawnshops, since those places attract distracted and vulnerable people who carry money and valuables [14], [17]. In other words, the environment of those places creates a crime opportunity. Therefore, relying on spatial discretizations such as the regular grids renders fine-grained crime analysis a quite challenging task, since the definition of a proper grid resolution and the identification of urban factors impacting the crime opportunity is not so straightforward when crimes are aggregated in a cell containing several street blocks. Even when a small grid resolution is used, the alignment of the grid cell, streets' segments, and other urban structures are not easy to do, hampering the detailed analysis of crime patterns and their possible causes. In addition, the grid representation also limits the analysis of the temporal behavior of crimes. For instance, suppose that a type of crime occurs consistently in a street corner during a period and, after a while, moves to a nearby corner. In a grid representation, such a temporal behavior can hardly be caught if both corners lie on the same grid cell.

In collaboration with domain experts, we designed *Mirante*, a scalable and versatile visualization tool tailored to explore crime data in a street-level of detail. Considering street corners as nodes and street segments as edges, Mirante assumes city street maps as the spatial discretization. Crime data is spatially aggregated on street corners using an *edge-node* strategy rather than Euclidean distance, which avoids several issues present in grid cell aggregation. Mirante provides a number of interactive resources to explore the spatial distribution of crimes and their dynamics over time, making it possible to identify temporal patterns such as the shift of crime hotspots among nearby locations. Interactive filters allow users to focus their analysis on particular hours of the day, days of the week, and months of the year, making it possible to easily scrutinize the seasonality of crimes. Using different selection mechanisms, users can interactively select regions of interest in various scales, enabling the spatio-temporal analysis of large regions as well as quite specific locations of the city, a trait not

[1] communitycrimemap.com [2] maps.nyc.gov/crime/ [3] crimegraphics.com
[4] crimemapping.com

available in most crime analysis tools. Simplicity and ease of use are other characteristics that render Mirante an interesting alternative in crime mapping.

In summary, the main contributions of this work are:

- A crime mapping methodology that relies on street maps as spatial representation, which allows the spatio-temporal analysis of large regions as well as specific locations of a city;
- Mirante, a simple web-based visualization tool that provides a number of interactive resources to explore and identify spatio-temporal crime patterns;
- Two case studies based on real data that demonstrate the usefulness of our methodology to reveal interesting crime-related phenomena in large and medium-sized cities in Brazil.

II. Related Work

In order to better contextualize our proposal, we focus the discussion on visualization methods to assist the identification and extraction of crime patterns from spatio-temporal data. Specifically, we organize this section in two main parts.

Crime Visualization Techniques. Different visual resources have been employed for exploring crime data, most of them combining augmented geographical maps and linked visual components. For instance, early approaches such as COPLINK [18] uses faded points on a GIS view combined with self-organized maps for clustering crimes. Buer et al. [19] employ a hillshade representation on each census block to express the density of crimes related to adjacent areas. Hotspot visualization has also been one of the major visual resources employed to analyze crimes, being Kernel Density Estimation (KDE), the main tool in this context. Good examples are VALET [20] toolkit, Hotsketch [21] that uses bisquare function as a kernel, MSKDE [22] that combines KDE and a marching squares strategy, and NKDE [23] that relies on a network-constrained kernel function. An alternative hotspot-based method is CrimAnalyzer [8], which makes use of Non-Negative Matrix Factorization (NMF) to compute hotspots, which, as a consequence of the NMF decomposition, splits hotspots according to their intensity and seasonality.

Although systems described above suit their purpose, they are not designed to enable a street level of detail analysis. As discussed in the introduction, the fine-scale analysis is fundamental for understanding certain phenomena, being this the main difference between our approach and those methods.

Street-level Visualization Techniques. Fine-grained analysis, as street-level ones are fundamental in crime mapping, as crimes usually occur in street segments [24], [25], they tend to recur in the same or nearby locations [15], and some specific urban sites such as bars and bus stations are where hotspots show up [26], [27]. Several visualization methods have been developed to enable a street-level analysis of different phenomena, most of which rely on mathematical and computational tools such as complex networks [28], [29], neural networks [30], [31], and clustering [32] to enable meaningful visualizations. For instance, StreetExplorer [33] uses line segment enhancing to search for patterns in urban street networks. VitalVizor [34] combines geometric entities such as streets, blocks, and buildings with parallel coordinates and tree diagrams to understand urban vitality. Wang *et al.* [35] rely on animation to explore sparse traffic trajectory data to visualize the movement of vehicles and extract flow patterns locally. Trajgraph [36] integrates a node-link graph view with a street-level map view for understanding urban mobility patterns. Graph measurements, such as betweenness, and closeness, are implemented to assist the analysis. SHOC [37], a visualization tool that presents different crime metaphors: point, choropleth, and kernel density maps (KDE and MSKDE).

Our approach builds upon simple but powerful visualization resources to enable a street-level detailed analysis. The implemented visual resources make the visual identification of crime hotspots quite precise and straightforward while providing interactive filtering mechanisms to explore temporal patterns, a trait not present in most of the methods described above. The simplicity and easy to use is another trait of our approach.

III. Requirements and Analytical Tasks

The development of Mirante has been a joint work with a team of sociologists with vast experience in public security and crime analysis. The sociologists are a well-known researchers in the study of violence in South America with large experience in public safety and social sciences applied to urban environments. Product of a number of meetings during a couple of years, we raised requirements that guided analytical tasks that are addressed by Mirante. Before presenting the requirements and tasks, we state some nomenclature used in the rest of the manuscript.

A. Nomenclature

Region refers to a geographical area such as a set of neighborhoods, streets, and parks. In our context, each region corresponds to a street network defined by the user.

Crime time series is a sequence of records of crimes in a particular place and aggregated by periods (*i.e.* by the hour).

Crime type refers to the nature of the criminal activity, typified according to the victim. In this work, we consider passerby, commercial establishment, and vehicle robbery.

Hotspots are locations where the number of crime occurrences is larger than in its surroundings. Since we rely on street map discretization, hotspots correspond to some street corners with a large concentration of crimes.

Crime Pattern is the prevalence of crime activities in a period. For instance, a place where crimes are prevalent for a period of time and then vanish.

B. Requirements

During regular meetings with the experts, it became clear their need for mechanisms to set the regions of interest in different scales (*i.e.*, neighborhoods and street segments). In particular, visually identifying street segment or street corners corresponding to hotspots were a major requirement, as their crime mapping tools did not allow them to scale down the analysis to a street-level of detail. Being able to switch the analysis based on the type of crime was also an important requirement. Understanding the spatial dynamics of hotspots and their patterns was important, as the available tools do not enable interactive filtering mechanisms to analyze the behavior of crimes over time. In summary, we point the major requirements as:

R1 - Selecting regions of variable sizes. Selecting regions of interest with variable sizes while maintaining the ability to perform analysis in a street-level of detail.

R2 - Identifying high hotspots. Identifying hotspots in a high level of detail in order to trace a relation between urban factors and crime.

R3 - Switch crime types. Crime patterns depend on the type of crime under analysis. Therefore, being able to switch between different types of crime is an important issue to compare crime behavior in a location of interest.

R4 - Crime Pattern Analysis. Understanding the dynamics of crime is a fundamental task in crime mapping. Therefore, identifying and exploring crime patterns is also fundamental to determine the urban factors that impact the emergence or eradication of crimes.

C. Analytical Tasks

The requirements described above gave rise to a list of analytical tasks that must be accomplished by the visualization tool.

T1 - Visualize hotspot in a street-level of detail. Enable visualization resources to reveal hotspots located in street corners and street segments. This task is related to requests R2 and R4.

T2 - Interactive selection of regions of interest. Provide interactive mechanisms to select regions of interest that range from whole neighborhoods to a few set of street segments, enabling analysts to focus their analysis on different levels of details. This task accounts for requests R1, R3, and R4.

T3 - Switch crime types in a given region. Filter the analysis of different crime types in a given region. This task achieves the request R3.

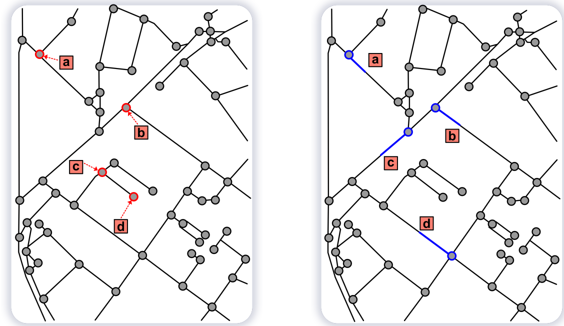
T4 - Show crime seasonality. Allow the exploration of crime seasonality, making it possible to filter crime occurrences according to periods of the day, day of the week, and month of the year. This task accounts for requests R3 and R4.

T5 - Identify crime patterns. Explore crimes based on specific time windows, thus uncovering hotspot patterns. This task helps achieve the requests R3 and R4.

Mirante integrates the tasks above into a meaningful and straightforward visualization tool. Details of Mirante's implementation is provided in the following section.

IV. Mirante

In contrast to most crime mapping techniques, which rely on regular grids as spatial discretization, Mirante represents the spatial component as a street-network, where street corners correspond to the nodes of the graph and street segments to the edges. Crime data is aggregated in each node of the graph and depicted as a graph-based heatmap when a region of interest is selected. The heatmap is updated according to filters that users can interactively apply to the data. In the following, we detail the construction of the graph corresponding to the spatial discretization, the design of the visual components, their functionalities, and implementation issues.



(a) Closest node strategy (b) Edge-node strategy

Fig. 1. Two ways to build a crime-based street-network by closest node based on: (a) Euclidean distance, and (b) edge-node strategy.

A. Building the spatial representation

To build the graph corresponding to the spatial discretization, we use the OpenStreetMap API [38], which allows for generating a street-graph containing roads and intersections for entire cities. It is possible to define the type of map to use, *e.g.*, pedestrian, bike, and car drive roads. We opt to use the pedestrian map, as it comprises drive roads and pedestrian walkways.

The number of nodes and edges derived from the map varies considerably depending on the city. For instance, the API returns a set of 533,437 vertices and 1,197,828 edges for São Paulo city — which we use in some of our experiments. However, a large number of vertices do not correspond to street intersections. To remove non-intersection vertices and all the points along a single street segment, we run a procedure (see [39] and corresponding implementation included in the OSMnx library) that topologically simplifies the graph. For São Paulo street map, the simplification results in 142,112 vertices and 415,178 edges, a considerable reduction that facilitate interactive procedures.

B. Assigning data to the nodes of the spatial graph representation

Let $L_{crime} = \{c_0, c_1, ..., c_n\}$ be a list of n crime records, where each c_i contains information such as record id (unique identifier), location (latitude, longitude), crime type, date, number of people involved, among other information. Let $G = (V, E)$ be the graph corresponding to the city's spatial representation. Each vertex has a unique geo-referenced coordinate (identifier, latitude, longitude), and each edge (set of points) represents a segment joining two intersections.

In our context, each crime record c_i must be assigned to a vertex of the graph G. The easiest solution would be to assign each c_i to its nearest vertex using the Euclidean distance.

TABLE I
METHODOLOGICAL AND VISUALIZATION PROPERTIES AND THEIR ANALYTICAL TASKS PRESENTED IN SEC.III-C.

	T1	*T2*	*T3*	*T4*	*T5*
Street-level heatmap View	✓	✓		✓	
Temporal Evolution View	✓			✓	✓
Temporal Histogram View			✓	✓	✓
Selector Toolbox				✓	✓
Address Search Bar	✓	✓			
Evolution Animation Controller			✓	✓	✓
Local/global crime ruler		✓	✓		

However, using Euclidean distance is not appropriate because it does not consider the topology of the spatial representation. We illustrated this issue in Fig. 1. Notice that using Euclidean distance the crime records "a" and "b" are properly assigned vertices, however, records "c" and "d" are not, since it is clear that the corresponding crimes took place on the street segments closer to them, so they should be assigned to one of the vertices defining the segments. Fig. 1b shows the correct procedure, which we call *edge-node distance*, where first, the nearest edge (e_{near}) is found and then the closest vertex.

The crime-vertex assignment starts by traversing the list of crime records L_{crime} to compute their nearest edge e_{near} in the graph G. Different strategies can be used to efficiently perform this step, *e.g.*, using a spatial data structure as Quad-tree or Ball-tree. In our case, we use an R-tree implemented in the OSMnx library ($e_{near} = G.get\_nearest\_edge(c_i)$). Once the nearest edge e_{near} and end-nodes ($(v_1, v_2) = G.get\_vertices(e_{near})$) is found for each record, it is assigned to the closest edge node. For that, we compute the distance to both nodes ($d_{\{1,2\}} = greatCircleDistance(c_i, v_{\{1,2\}})$) and crime record in c_i are stored into the list $crimes$ associated to each node, that is, $v_1.crimes.append(c_i)$ if $d_1 < d_2$ or $v_2.crimes.append(c_i)$ otherwise. List per-vertex is used to temporally aggregate crime records (hourly aggregation in our case), giving rise to a time series associated to each vertex.

To alleviate memory usage, we store the graph and note time series into a PostGIS-PostgresSQL database, allowing us to perform querying/retrieving operations quite efficiently.

C. Visualization Components

Mirante brings a set of fully-linked visual components for supporting the exploratory analysis of crime data in a selected region. Fig. 2 shows the Mirante system and its seven main visual components: (a) street-level heatmap to visualize the crime hotspots in a region; (b) temporal view showing the time evolution of the crime; (c) seasonal histogram view depicting the seasonality of crimes by a period, day, and month; (d) selector toolbox that enables different approaches to select regions of interest; (e) a search bar to select regions of interest based on addresses; (f) an evolution animation controller; and (g) a local/global crime ruler. We design the visual components to fulfill the requirements raised from the interaction with domain experts, thus addressing the analytical tasks described in Sec. III-C. Table I details the relation between visual resources (first column) and tasks (T1-T5 columns).

Street-Level Heatmap. This view, depicted in Fig. 2a, seeks to summarize the distribution of crimes across the city by displaying a set of colored segments on streets using the number of crimes assigned to each vertex of graph G. For each vertex, we match a color from a palette depending on its stored value, as illustrated in Fig. 4a. Given the continuous nature of our data, we use a sequential scale — starting in dark red to light yellow — taken from ColorBrewer 2.0[5]. Then, we use linear interpolation for coloring the lines representing the edges (see Fig. 4b).

Temporal Evolution View. This view uses an interactive line chart for displaying how crime events evolve in the selected region (see Fig. 2b). Moreover, this view can filter the analysis to focus on a specific range of time, which can be selected by dragging a range window along the x-axis. Once a new range of time is selected, all linked views are updated accordingly.

Temporal Histogram View. It comprises four bar charts that detail the crime distribution in the period of the day, day of the week, and months of the year (see Fig. 2c). On the top, the red bars show the volume of crime types in the selected region. On the bottom, on the left histogram (orange bars) show data aggregated by the month, while on the right, the bar charts visualize data by day of the week (in yellow) and the period of the day (in dark red). Each bar chart serves as a filter, that is, if a user clicks on one of the bars, all views are updated to show only crime occurrences in the selected filter.

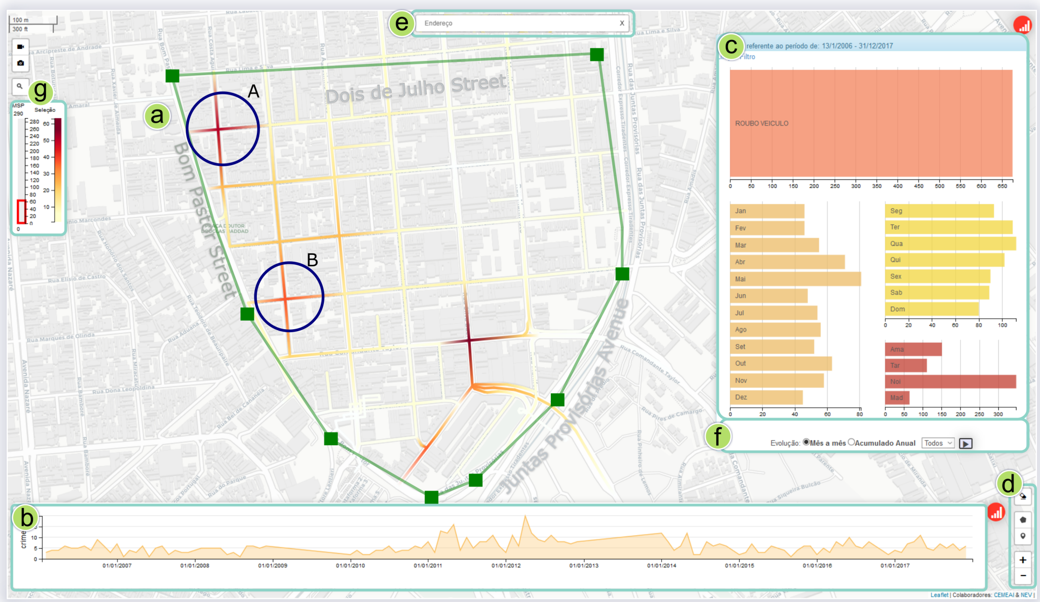
Selector Toolbox. We implement two different types of area selection: i) *Radial-centric area selection*, which sets a geographical coordinate as the center and allows the user to interactively define a radius in meters (see Fig. 3a). ii) *Polygonal area selection* that allows users to draw a polygon enclosing a region of interest (see Fig. 3b). The selectors are in the bottom-right part of the screen (see Fig. 2d).

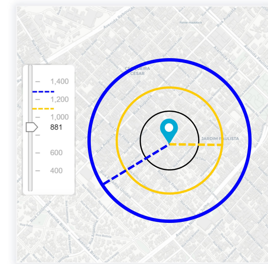
Address Search Bar. Users can also define a region of interest based on the address search bar that uses Google GeoSearch Engine[6] to query for the address that most closely matches the one typed by users (see Fig. 2e). Once retrieved, the system automatically defines the region of interest as disk centered in the given address.

Evolution Animation Controller. Mirante allows the analyst to inspect, through an animation, how data evolves over the months of the year. The analyst could choose to animate by month separately or cumulatively (Fig. 2f). Each time-series reveals different crime behavior in the chosen geographical location, which are also shown as heatmaps (top images).

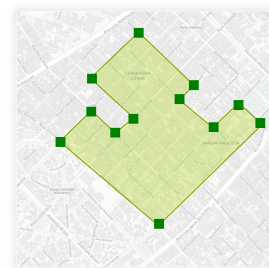
Local/Global Crime Ruler. One of the main issues when performing local analysis is to figure out how criminal activity observed in the region of interest compares with the amount of crime recorded in the city. To tackle this issue, we use two rulers, the global one that shows how the more intense hotspot of the selected region compares against the more intense hotspot in the whole city, and the local ruler that shows the color map used to highlight hotspots in the selected region (see

[5] https://colorbrewer2.org/ [6] https://github.com/smeijer/leaflet-geosearch





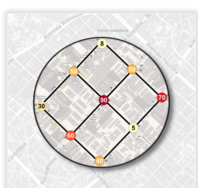
(a)



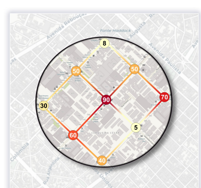
(b)

Fig. 2. An overview of the Mirante tool, a set of spatiotemporal visual resources enabling the exploration of crime patterns in a region: (a) Street-level Heatmap, (b) Temporal Evolution View, (c) Temporal Histogram View, (d) Selector toolbox, (e) Address Search Bar, (f) Evolution Animation Controller, and (g) Local/global crime ruler.

Fig. 3. Two different types for selecting a region of interest: (a) based on its center and a radius, and (b) by drawing a polygon.



(a) Color assignation



(b) Linear interpolation

Fig. 4. Street-level heatmap construction: (a) Match of color with crime intensity for each node, and (b) Linear interpolation for coloring all edges between each two adjacent vertices

Fig. 2g). The rulers allow users to figure out how "dangerous" it is the region of interest compared with the whole city.

D. Implementation Details

Mirante is a web-based application implemented under the Django[7] framework. The core of the system comprises data modeling and visualization modules. For the street network, we used OSMnx[8] and NetworkX[9] python libraries to process data. We achieve interactive rates in computation of the nearest edges, vertex nodes, and street network simplification. All visualization resources have been developed using JavaScript libraries: Leaflet[10] to perform the interpolation geo-map and D3.js[11] to represent line and bar charts. In our case, we have developed extra components to manipulate filters by using Crossfilter[12] and Dcjs[13] libraries.

[7] https://www.djangoproject.com/ [8] https://osmnx.readthedocs.io
[9] https://networkx.github.io [10] https://leafletjs.com/ [11] https://d3js.org/
[12] https://square.github.io/crossfilter/ [13] https://dc-js.github.io/dc.js/

V. Case Studies

In collaboration with domain experts, we conduct two case studies to assess Mirante's performance in terms of effectiveness for pattern identification and navigability. We analyze two types of crimes in two different Brazilian cities with very different characteristics: São Paulo, the largest city in South America, and São Carlos, a medium-sized city in the state of São Paulo. Both data sets were geo-coded and provided by the police department of São Paulo and São Carlos, respectively.

A. Vehicular Robbery in São Paulo City

In this first case study, we assess the usefulness of Mirante as its effectiveness in identifying vehicle robbery patterns in a given region of São Paulo. The main task is to understand the impact of changes in the local urban infrastructure in the crime opportunity.

São Paulo's road structure is not properly constructed and maintained. The analysis aims to support a crime pattern theory that suggests a higher risk of car robbery/burglary is linked to the road infrastructure. Roughly speaking, there is a correlation between the distribution of crimes and the urban road infrastructure.

To accomplish the case study, we select a region in the south part of São Paulo. This region is near a *favela*, *i.e.*, a neighborhood of low income, and unregulated settlements. Using Mirante, we draw a polygon comprising the streets: *Bom Pastor Street*, *Juntas Provisórias Avenue*, and *Dois de Julho Street* (see Fig. 2), which accounts for task T2 (see Section III-C). Known as a region with a large number of vehicle robbery, we focus the study on this type of crime (task T3). The selected region contains approximately 650 occurrences of car robbery in the period 2006 to 2017.

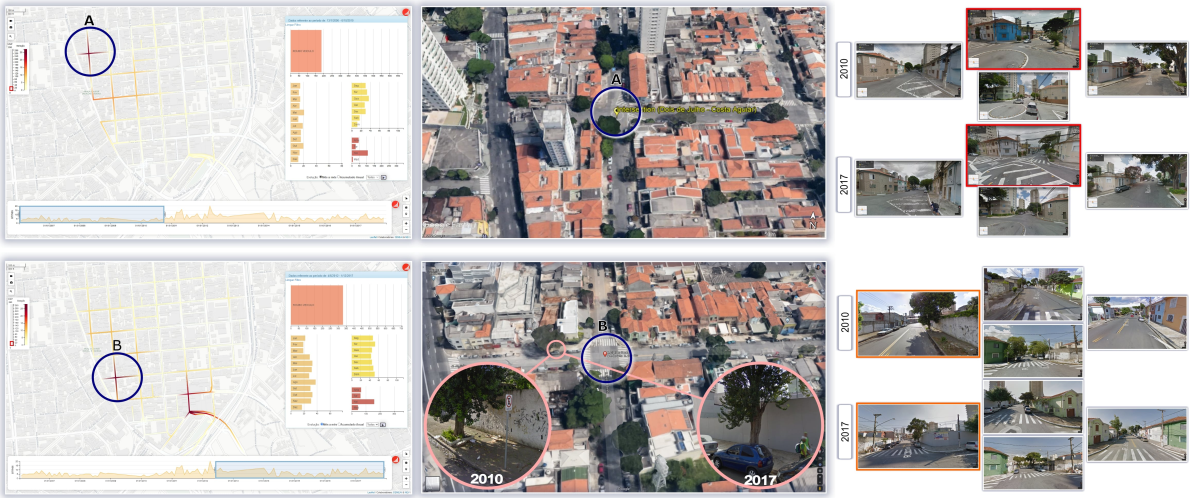


Fig. 5. Vehicle robbery patterns around São Paulo city: (First-column) Crime behavior using *Temporal Evolution View* selecting two periods of time, one from to 1/2006 to 11/2010 and another from 11/2010 to 12/2017. (Second and Third columns) *Google Street View* images of highlighted nodes in different years and from different angles.

Exploring the *Street-Level Heatmap View*, we note two hotspots labeled as “A” and “B” in the Fig. 2 and first column in the Fig. 5 (task T1). Using the *Temporal Evolution View*, we filter crimes from 2006 to November 2010. In this period, a single prominent hotspot shows up in the northwestern region of the region (top image in the first column of Fig. 5). Note in the temporal view that the number of occurrences decreases at that location in that period, but, from 2011 on, crimes present an increase (tasks T4 and T5), and the new prominent hotspot shows up on the southwest of the region, marked as “B” on the bottom image in the first column of Fig. 5.

In particular, we conduct an empirical analysis examining the urban infrastructure in the hotspots’ surroundings employing Google Street View to retrieve and display photos in the two-time intervals used in our analysis (see the second column of Fig. 5). The photos suggest that the risk of burglary might be related to the parking areas and vertical/horizontal transit signs.

In the first case (hotspot “A”), there is an evident change in the horizontal transit sign (see the third column on the top in Fig. 5). Specifically, notice in the red photos that the roundabout that was present in 2010 was removed in 2017, forcing drivers to take specific directions, what could make it harder for criminals to quickly escape to the main avenues that border the region of interest, thus triggering a decrease in the number of car robbery in the hotspot “A”.

Regarding hotspot “B”, notice in the orange photos that in 2010 it was not allowed to park cars on the right side of the street, and in 2017, the parking was allowed. The direction where cars were allowed to park goes directly to a main avenue that connects, a hundred meters ahead, to an urban highway, thus making it easy to steal a car and quickly escape down the highway (see on the larger photo on the right in Fig. 5 the connection with a main avenue).

B. *Passerby Robbery in São Carlos*

The second case study involves passerby robbery in São Carlos, a mid-sized city in the interior of the State of São Paulo. In a series of meetings with authorities in charge of the public security in the city to demonstrate Mirante’s capability, the authorities presented public policies implemented in the city to reduce criminality over the years. Despite the reduction in the number of crimes, mainly passerby robbery, it was not clear to the authorities which actions impacted most in crime reduction. Aiming to give some answers, we used Mirante to explore crimes over the city, describing one of our findings in the following.

Specifically, security authorities would like to know whether improvements in the urban infrastructure impact the crime rates, mainly passerby robbery (task T3) in one of the main avenues of the city in the interval from January 2014 to April 2019. Using the selection resource to explore the avenue, one particular site called our attention. Selecting the region of interest using a disk of radius 300 meters (task T2) and choosing three time intervals in the temporal view (tasks T4 and T5), we analyzed the behavior of crimes on three time intervals considering the period of the day with the most prevalent crime rate, as depicted in Fig. 6. We also use some images from the Google Street View to verify which factors could be contributing to the increase or decrease of crimes in each time interval. Figs. 6 (a, b, and c) show the *Street-Level Heatmap* (task T1), selected time interval in the *Temporal Evolution View*, *Temporal Histogram View* (tasks T4 and T5), and a photo that was taken in the years where the time intervals have been chosen, namely 2015, 2017, and 2019, respectively.

Fig. 6a-(*Temporal Histogram View*) shows that in 2015 crimes were most frequent in the afternoon (blue rectangle). According to the Google Street View photo, no people are living under the viaduct. However, domain experts alerted that during the afternoons, the viaduct became a point where marginalized people used to get together, which can explain

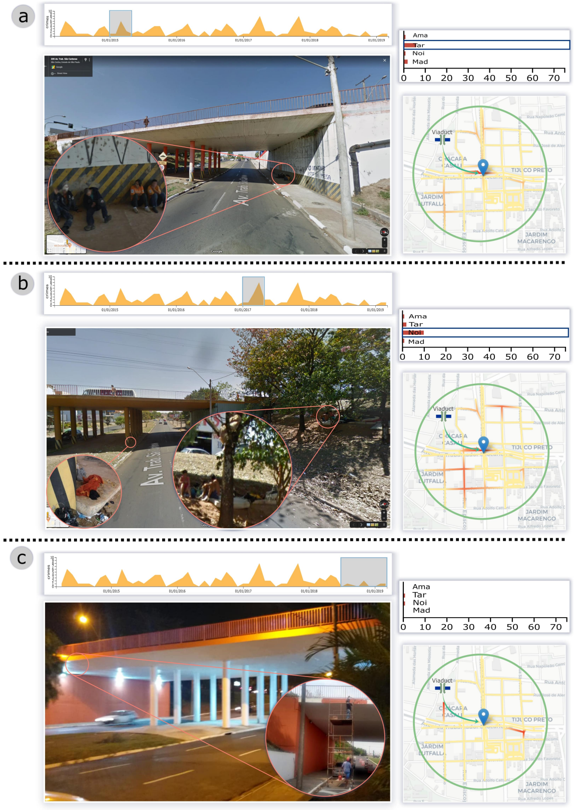


Fig. 6. Urban infrastructure impacting in passerby robbery in São Carlos city: (a), (b), and (c) *Street-level Heatmap*, *Temporal Histogram View* showing the seasonality of crimes, *Temporal Evolution View* with selected time intervals, and Google street view images respectively.

the large number of passerby robberies in that period of the day. Fig. 6b-(*Temporal Histogram View*) shows that in 2017 crimes were more frequent in the evening and, according to the Google Street View photo, homeless people were living near the viaduct, which might explain the large number of crimes in the evening. Fig. 6c-(*Temporal Evolution View*) shows a significant drop in crime rates by the end of 2018 and the first quarter of 2019. According to the photos, the region around the viaduct was revitalized in that period (facade, lighting, etc.), making the region safer. Notice that the decrease in the number of crimes is clearly shown in the *Street-Level Heatmap*. The authorities speculate that the improvements in the infrastructure might explain the decrease this event.

São Carlos's security authorities considered Mirante a valuable tool for different types of analysis. In particular, it supported the hypothesis that improvements in infrastructure can help to reduce crime rates in specific locations. They have also pointed out the capability of Mirante to highlight hotspots in a street-level of detail, a functionality they do not have in the crime mapping systems they use to play with. They explicitly said that Mirante is a very interesting analytic instrument that could be quite useful in several scenarios.

VI. Expert Feedback

After using Mirante and conducting the case studies, two experts gave us some feedback. The first paragraph is from the sociologists that used Mirante to analyze crimes in São Paulo (called *E1*). The second paragraph is from São Carlos's security authorities (called *E2*).

E1: *"The proposed tool has enabled an alternative solution to the challenges we face in our daily analysis. First, modeling the spatial domain in a street-level of detail makes easier the understanding of the spatio-temporal characteristics, with good implications for public security and social interrelationships. Second, through visual analysis, Mirante motivates the study of a variety of crimes. Mirante's visual resources make it possible to analyze the dynamics of crimes and their relation with urban factors. Third, each city has its complexity; based on our experience, a city usually brings together diverse places (violent and peaceful). This fact makes global studies less productive due to the lack of local details. The proposed tool enables a focused analysis while preserving the relation between local and global crime rates."*

E2: *"This research is benefiting our city; it is a critical and unprecedented investigation. Our security professionals already work with crime analysis techniques. However, this crime mapping tool allows a more in-depth and detailed analysis of crime patterns in specific regions. With Mirante's results, we can define actions to reduce crime rates in specific areas. For instance, we could adopt primary interventions such as the improvement of lighting and traffic-flow or police forces interventions."*

In both cases, we got positive feedback from the users. The experts explicitly mentioned that their current tools do not manage to do the same analysis as Mirante.

VII. Discussion and Limitations

We constructed the visual resources guided by the requests and analytical tasks of domain experts described in Sec. III. However, there are some limitations and research opportunities identified during the design and implementation processes.

Integration with Google Street View. As evidenced in both case studies, urban infrastructure has an important impact on crime rates. Such a finding was possible due to Google Street View, which was used as a side tool. We are planning to integrate Google Street View API with Mirante, enabling a more comprehensive exploratory analysis.

Street-Network Topology. As detailed in Sec. IV, it is possible to make use of different street maps. In this work, we use pedestrian walkway maps to derive the graph that supports our spatial discretization. However, a unique network for various crime types could lead to misinterpretations. As future work, we will implement a resource to allow users to switch spatial representations on the fly.

Multiple Data Sources. A limitation of Mirante is that it only plays with a single source of data, crime data. However, a more insightful analysis could be performed if other sources were made available. For instance, providing mechanisms to enable the joint analysis of crime and flux of people could result in much richer outcomes. How to integrate multiple data sources into Mirante is a challenge we are currently facing.

VIII. Conclusion

In this work, we introduced Mirante, a visualization tool tailored for crime data analysis. Mirante relies on street maps as spatial discretization, and it enables a set of fully-linked visual resources to filter crime data based on temporal patterns and seasonality. Enabling street-level of detail analysis is a particularly important trait of Mirante that is not available in most crime mapping systems. The provided case studies show the effectiveness of Mirante in identifying crime patterns, making it easier to establish relations between crimes and other factors, such as urban infrastructure. Mirante has been evaluated by experts in public security, who gave us quite positive feedbacks, attesting the usefulness of our methodology.

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