Beyond Authoritative Safety Assessment: Applying Geospatial Technology to Explore Perceived Safety in Baton Rouge, Louisiana

Final Research Report MARSHALL PLAN SCHOLARSHIP

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Abstract

Nowadays, spatial crime analysis, modelling, and predicting by using GIScience methods and other technical developments have developed into an interdisciplinary branch of research. Such integration of a multitude of methods has improved, among others, the quality and understanding of urban safety. However, the implications of these developments at the level of knowledge construction within communities, still need to be explored. This project discusses a new methodological approach contributing to the knowledge of an urban environment's complex composition. Using previous research in the city of Krakow, the present study aims to integrate the capabilities of spatial video techniques, geonarratives, and skin measurements (moments of stress) in detecting safety parameters in the city of Baton Rouge. Benefits and limitations of such technologies will be studied in detail. The data acquired have semantic value and are used to reveal the following information: visual, audio and physiological, with matching timestamps and GPS coordinates for spatiotemporal applicability. Furthermore, the results of data processing are joined with official (objective, reported) crime data, which shows density relationships between perceived safety vs objective (reported) safety.

Keywords: crime occurrences, perceived safety, moments of stress, geonarratives, urban studies.

Notes:
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1. Introduction

The application of geospatial technologies in researching spatial crime patterns started in the US in the second half of the 1980's (LeBeau and Leitner 2011). During the same period, studies started focusing on the safety of urban neighborhoods. Jacobs and Newman were pioneers in the study of urban planning in relation to issues of safety (Newman 1996, Fuller and Moore 2017), contributing to the creation of the criminology sub discipline called Crime Prevention Through Environmental Design (Casteel and Peek-Asa 2000). Thus, safety issues in an urban environment define a complex concept studied in various fields. Moreover, the concept of fear of crime is an important urban problem included in the safety perception that affects the quality of life in cities.

Urban Planning and Environmental Criminology are two fields connected in studies for a new perspective in safer cities (Cozens 2011). A way to determine safety perception is through the so called Safety Perception Surveys (Jones-Lee, Hammerton et al. 1985). The terms "mental map" and "cognitive map" are used as metaphors, defining collections of methods applied for extracting perceptual elements (e.g. a mental map of the neighborhood).

Research consistently indicates that actual crime occurrences and the perceived fear of crime in urban areas are key concerns for society and that safety is highly important for sustainable environment (Lewis 2017). In the same time, researchers found that fear of crime tends to occur at higher rates than reported crime occurrences (Carvalho and Lewis 2003). While debatable in the previous research body, one study has shown that the perception of safety in a campus environment correlated with actual crimes, which helped to better implement safety improvements within the campus landscape (Fernandez 2005). Much research focused on discussing police perceptions and neighborhood citizens opinions on crime and rarely the two parts were compared (Dowler 2003). There are various attractors for safety-crime perception, similar to the environmental theory of crime patterns, including crime attractors, generators and detractors (Brantingham and Brantingham 1995). An element which can be influential for crime perception is urban blight or urban decay. Urban blight refers to the phenomena when a part of a city or a specific area, starts to be neglected for various reasons. Signs of blight are abandoned buildings or desolated areas, all these elements being highly visible at micro scale.

Due to the interest of this research on safety and crime occurrences, and additionally the presence of urban blight, Baton Rouge, Louisiana was selected as a case study. It is worth mentioning that Baton Rouge has history regarding its crime rates. The murder rate in Baton Rouge for 2011 was the eighth highest in the nation among large cities and had the 25th highest violent crime rate in the U.S. in 2011[1]. Popular in the last years is the creation of Crime Prevention and Improvement Districts (CPID's) in Baton Rouge[2]. These districts are created when citizens from a specific geographic area pay more taxes

[1] https://www.fbi.gov/about-us/cjis/ucr/crime-in-the-u.s/2011/crime-in-the-u.s.-2011/offenses-known-to-law-enforcement/standard-links/city-agency
[2] https://www.businessreport.com/realestate/crime-prevention-districts-baton-rouge

to fund off-duty police patrols and beautification projects. Ronal Serpas, criminology professor at Loyola University, California, considers that the general perception of inhabitants is that police presence would make the neighborhood safer. However, there are no clear statistics yet showing if this is valid or not.

Based on a thorough literature review, research shows the need of more detailed and complex information for urban safety and security, whether subjectively vs objectively collected. Quality of life is affected by crime, fear of crime, and anti-social behavior, which are valuable indicators in people's choices for living (Colquhoun 2004). The general mission of this project is to document the use of emerging technologies to explore urban safety. Methods are required to collect contextual information in a standardized way and in a format that can be archived, so that they can be used in long term and comparative studies.

1.1. Research questions and objectives

This project is an approach to amalgamate the knowledge about safety features already studied in the urban environment. The study design is data-driven, thus resulting datasets may be used for many purposes. However, the primary goal of this work is in using a fusion methodology for integrating a systematic video data acquisition, geographical storytelling, and human physiological measurements to build upon the analysis of urban environment through a GIS-based platform.

The three main objectives of this project are:

(1) to test the compatibility of data acquisition through mixed technologies;
(2) to extract safety information from the data acquired using mixed methods and to implement it in a GIS-based model;
(3) to compare official crime data reported to the police, urban blight indicators and people's perceived safety, extracted from the mixed-method approach.

This research is based on a mixed-method approach, adapting and evaluating the use of geospatial technology, including spatial video, geo-narrative, and skin-conductive wristbands, to identify perceived crime and its correlation with objective (official reported) crime and urban blight. By doing so, as a long-term outcome, we would like to contribute to improving citizen cooperation with official stakeholders and help to design crime prevention strategies. In addition, traditional surveys are applied to participants. This report is showing partial results resulting from data processing, emphasizing the importance of the study and the power of the chosen mixed methods approach. All the data collected will be analyzed in the frame of an impact factor journal manuscript. It is important to mention that two strongly connected works were conceived at similar time, however with two different aims. First aim considered the extraction and standardization of urban blight indicators (Stratmann 2019), while the second aim focused on safety perception. Whereas this report presents information for the second aim, the authors worked together in both projects, with different percentage of involvement.

2. Related work

The connection between space, time, and semantics has been developed in most recent years due to the huge amounts of data and metadata. Mixed-methods approaches started to be highly used in diverse research fields. The rationale of this research starts from the hypothesis that emerging human generated data from wearable sensors, social media text and image analysis, mobile phone, and others represent geospatial processes. A short summary of works dealing with (geospatial) videos, audio/text and biosensing is presented in the next rows.

Nowadays extracting information from big amount of data covering videos and pictures is highly studied by using new methods, such as convolutional neural networks. For example, a large study called Place Pulse 2.0 has the objective to collect human perception on images from 56 cities from 28 countries across 6 continents, by using six evaluative questions about which place looks safer, wealthier, more beautiful, more boring, livelier or more depressing – six psychological feelings for urban perception (Dubey, Naik et al. 2016). The pilot study integrated results from three questions and was validated with data on violent crime for New York City (Naik, Philipoom et al. 2014), finding that the measures of urban perception from the study correlate with violent crimes after controlling for the income, area, population and average age of each NYC zip code.

Spatial video technology allows the acquisition of video data that includes information about the geographical location of each recorded frame. Research includes the application of spatial video technology and its integration into GIS to understand outdoor smoking patterns on campus (Burke, Cinderich et al. 2015), post disaster recovery (Mills, Curtis et al. 2008), health (Curtis, Curtis et al. 2015), built environment, graffiti collection (Krauthausen, Leitner et al. 2019) and roadside advertisements (Strelnikova, Schneider et al.). Using SVAS technology enables the ability to survey the same location multiple times for analyzing spatiotemporal phenomena, for example the safety level of a neighborhood. Another highly used way to determine safety is through so-called Safety Perception Surveys (Jones-Lee, Hammerton et al. 1985). However, unlike this survey method, our approach generates visual data that can be archived and re-analyzed in GIS-related or alternative environments (Mills, Curtis et al. 2010, Curtis, Curtis et al. 2018).

Geonarratives are stories from recording devices with timestamp enabled. Research shows that geonarratives considering space and time are used for: highlighting "therapeutic landscapes" incorporated into people's lives to maintain a sense of well-being (Bell, Wheeler et al. 2017), comparing geographical context through sketch maps provided by ex-offenders to identify high-crime areas in their communities (Curtis, Curtis et al. 2018), understanding people's everyday practices and routine place encounters (Bell, Phoenix et al. 2015), analyzing case studies in post-disaster recovery, crime, mosquito control and tuberculosis in the homeless (Curtis, Curtis et al. 2018).

Environmental studies may draw interest in the geonarratives or geostories that enable to define people's perceptions verbally. They add additional context to visual and feelings perception and can

be used in correlation with social media text processing. New research coins the term "spatial video geonarratives" (SVG) - the integration of the spatial video and the recording audio (Curtis, Curtis et al. 2018), which will also be followed in the present project.

In order to collect citizens feelings a growing number of eDiary apps have been introduced that measure location, timestamp and context through questions for the user at defined times for defined purposes (Zeile, Resch et al. 2015, Zeile, Resch et al. 2016). These citizen centric perspectives can then be correlated with additional social data, such as social media, and create purpose-defined indicators (e.g. well-being indicator). Wearable sensors, such as wristbands, are used in research for measuring psychophysiological parameters for different approaches, such as identifying places in urban environments which are perceived as unsafe by cyclists (Zeile, Resch et al. 2016). Recent research shows the development of methodologies of extracting moments of stress (MOS) from the capabilities of wearable sensors (Kyriakou, Resch et al. 2019). The authors are verifying their algorithm with laboratory experiments in order to understand physiological responses to various types of stressful elements. However, so far little research has been done on the additional benefit of physiological sensors for urban safety or fear of crime. Moreover, little to no research collected moments of stress and perceived safety on the field consecutively. Thus, this research implements the MOS algorithm together with the other mixed methods in order to find relationships and understand people's perceptions about safe and unsafe locations.

This proposed research extends previous studies in the urban environment by using emerging geospatial technologies, including the Spatial Video Acquisition Technology (SVAS) (Mills, Curtis et al. 2010), the geonarrative approach (Curtis, Curtis et al. 2015), and skin conductive wristbands (Resch, Summa et al. 2015, Kyriakou, Resch et al. 2019) that have the ability to identify people's emotions. All acquired data are subsequently fused into a GIS environment, and their interpretation will complement methods for spatial crime analysis and urban safety.

While the approach can be designed for any urban area to answer spatiotemporal questions, this proposed study intends to explore the fear of crime in the city of Baton Rouge that has a history of high crime rates. This study compares the official spatiotemporal information about criminal activity from the Baton Rouge Police Department (PRPD) with the perceived safety, all integrated in a GIS environment.

3. Data and Methods

This research design is applied in Baton Rouge, the capital city of Louisiana (United States), part of East Baton Rouge Parish (EBRP). The EBRP consists of four cities: Baker, Central, Zachary, and the City of Baton Rouge.

Baton Rouge includes 58 neighborhoods and occupies a 123,84 sq km area on the east bank of the Mississippi River. According to the most recent census data, the city has 229,493 inhabitants, declining to 225,374 in the final year of 2017 according to the Population Estimates Program. The ethnical diversity is not balanced, most of the residents are African American (54.8%), whereas white residents make up ~36.6% of the population.

3.1. Data acquisition

3.1.1. Online resources

Crime data retrieval was done from the Baton Rouge Police Department (BRPD), including coordinates and time stamp of the occurrences. Due to missing coordinates or even addresses we applied geocoding over the crime dataset in 2018. Initially the East Baton Rouge Parish had 45,561 crimes in the database for 2018, from which, after geocoding and cleaning became 44,964 record. From this number the points within the City of Baton Rouge limit are extracted and the final number of records is 44,554.

Consequently, other additional exploratory data, are considered in the study, as well: 311 Call for service; Census data: residential population, ethnicity, education, household types, foreign born, unemployment, poverty rate; Environmental data: street network, buildings footprint, public buildings, neighborhoods, etc. The newly collected information (safety perception from spatial video analysis, sentences/words from recorded interviews and individual emotions) will be tied to locations on the map and visualized on top of crime locations using GIS.

3.1.2. Survey data

As a first step we created a survey (Appendix 1) in order to collect basic information database for perceived safety and the implications of urban blight in it.

The survey includes (1) a questionnaire about crime perception in Baton Rouge and (2) an on-screen mapping exercise that is implemented in Google Maps. We asked the participants to draw polygons, lines or points in the city of Baton Rouge map and give a short description why do they feel unsafe in those specific locations. Each layer was saved as *.kml or *.kmz for easy import in any GIS software. The GIS layers can be merged for an average overview and a density map of unsafe areas in the city. Analyzing the data of the mapping exercise is not part of this report. Appendix 1 is attached at the end of the report. We conducted two pre-tests to make sure the survey and on-screen mapping are

positive. The average time for both actions was about ten minutes. The surveys were sent by email, part of the participants filled them inside the classroom and other part outside the classroom. They returned the completed documents per email.

3.1.3. Field work

After having the results from the survey, we started designing a route to follow with each participant, while capturing video, audio and physiological measurements. Before deciding on the route to follow, we worked on a complementary project, briefly discussed below. Stratmann (2019) explores urban blight and its correlation with crime rates in Baton Rouge (Stratmann 2019). Qualitative and quantitative data are collected in selected neighborhoods with a high, medium, and low crime density, by using the same SVAS. The selection criteria for the neighborhoods included various factors, to name a few: no or low number of highways, no or low amount of water bodies, connectivity as much as possible between neighborhoods, similar length of street network, five classes of crime intensities. Before getting engaged in the field work the shortest path for driving in the neighborhood was determined.

After collecting videos from all the streets in five neighborhoods from the city, blighted locations were manually digitized. One blight location can consist of more blight indicators and can get a weight of 1 (low blight level), 2 (medium blight level) or 3 (high blight level), depending on the degree of blight (Stratmann 2019). Physical blight indicators are defined: B1=abandoned buildings, B2=broken window/door, B3=blocked window/door, B4=no window/door, B5=building graffiti, B6=structural integrity, B7= building overgrowth, B8=other (building); E1= Damaged sidewalk, E2=damaged road, E3=overgrown vegetation, E4=litter, E5=illegal dumping, E6=unkempt area, E7=illegal parking, E8=abandoned vehicle, E9=infrastructural graffiti, E10=other. A total of 1717 urban blight locations were digitized where each location contains multiple indicators. 69% of the indicators are environmental/infrastructural blight and 31% are property blight indicators (Stratmann 2019).

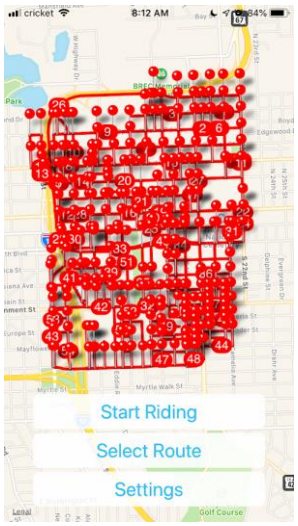

Figure 1. Example from the GPS app used for the spatial video routes in the urban blight data collection

Route

After having the urban blight digitized database, we followed consequent steps in order to define a suitable route for the safety perception collection, which was followed with each one of the participants. We tried to find a route that does not take more than 30 minutes' drive, includes high and low-moderate crime rate areas, different economic status, availability of residential areas connected without masks of lakes or highways, spatial proximity of high and low urban blight densities. For this safety perception analysis, there are at least three people in the car, including a driver, an interviewer and a participant of the empirical study (Curtis, Curtis et al. 2015) – for the urban blight selection there were no participants needed, only the driver and an additional researcher. Data acquisition took place in April 2019.

Practically, the route was driven by a car in an urban environment (city of Baton Rouge, LA), together with a test subject (participant) at a time (Figure 2). The car was equipped with the spatial video technology and recording devices, and the participant was wearing an Empatica E4 wristband, measuring various physiological measurements. We had 44 student participants. As mentioned previously, before the fieldwork participants had to fill in a survey about safety perception in Baton Rouge. In this report we are showing results only for ten participants for the experimental design.

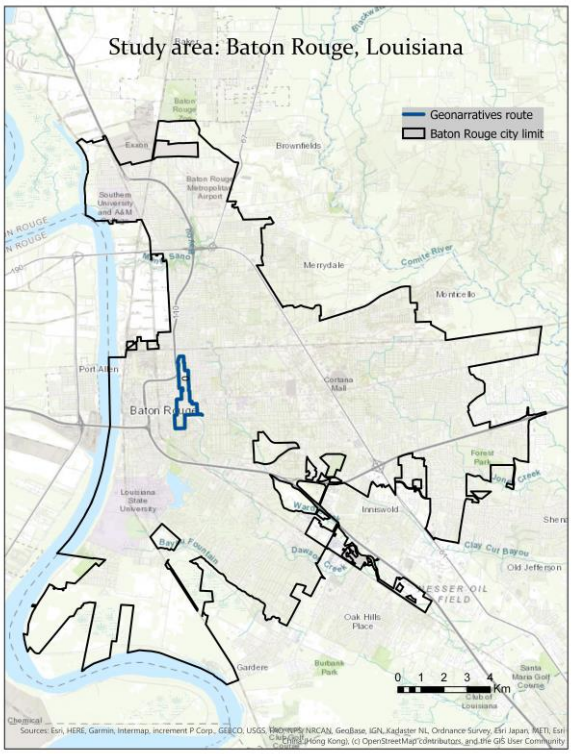

Figure 2. Study area and the Geonarratives route

Spatial video

The streaming videos are collected using the Spatial Video Acquisition System (SVAS), or spatial video, which allows to gain an on-site point of view, and can be applied to various types of research that demand impartial visual information (Mills, Curtis et al. 2010). Unlike Google Street View, SVAS data collection is in the control of the researcher. Spatial video can be collected using a variety of modes (car, motorbike, bicycle, boat and by foot). This system can record videos from a survey vehicle in the direction of travel with one or more cameras (Lewis, Fotheringham et al. 2011). Having just one camera in front can be insufficient, because it cannot detect the side angles. This is the reason why additional cameras are recommended. At the present time, there are no standards discussing spatial video format, resolution or type of storage database. Research shows application of spatial video technology and integration in GIS to understand outdoor smoking patterns on campus (Burke, Cinderich et al. 2015), post disaster recovery (Mills, Curtis et al. 2008), health (Curtis, Curtis et al. 2015), built environment , roadside advertisements (Strelnikova, Schneider et al.).

The spatial video recording was conducted with the use of five Contour cameras[3], four of which will be attached to the side windows at the back of a car, and one will be mounted on the windshield, as discussed by (Strelnikova, Schneider et al.), excepting the second set in the back.

The two main components of a SVAS are the digital video camcorder with an integrated Global Positioning System (GPS) receiver that allows the collection of spatially referenced digital video material. We used the Contour+2 Action Camera Model 1700 in this research to collect the video material. It includes a 170 degree wide angle lens, which is favorable for narrow streets. It can also be connected to other devices. The Contour +2 cameras contain an internal microphone, however an external microphone or a recorder (Figure 3) can be used to provide better quality recordings since there are many background noises in the car.

Figure 3. Audio recorder

[3] http://contour.com/

Videos are recorded in high definition (1080p) and run at 120 frames per second. The produced files are embedded with GPS locations; each frame of the video is tagged with a coordinate. Each camera can record a file every 40 minutes with the size ~4GB, and it needs a memory card with enough free space for it. Subsequent data collection routes might be revisited in case of collection problems or in case of compiling temporal comparisons for the same place.

Using SVAS enables the ability of surveying the same location multiple times for analyzing spatiotemporal phenomena, namely safety level for our approach. Another highly used way to determine safety is through the so called Safety Perception Surveys (Jones-Lee, Hammerton et al. 1985). However, unlike the survey method, our approach generates visual data that can be archived and re analyzed with other research questions, in GIS related environments or other types (Mills, Curtis et al. 2010, Curtis, Curtis et al. 2018).

Figure 4. Contour cameras used for the spatial video collection

Geonarratives

Place is used to stimulate discussion (Curtis, Curtis et al. 2015), namely on a specific route study participants will talk about their opinions and experiences, while also the spatial video is connected. The audio recording of this narrative is linked to the video via timestamp, creating as such the Spatial

Video Geonarrative (SVG). We defined an unstructured interview during the 30 minutes route between the interviewer and the participant. The reason why we did not follow and exact structure is because each participant has a different familiarity and opinion about the surveyed area and not only, thus expressing themselves in a diverse way. The audio recording is called geonarrative and it is transcribed to text for further analysis. The geonarrative gives contextual details and enriches typical hotpot approaches with more on-the-ground context. It can be considered similar to mental map from behavioral geography, giving multiple perspectives for the same geographic area.

Conductive skin-wristbands

Empatica E4 wristbands are used in this research for measuring psychophysiological parameters, adding context to feelings perception. Practically, the study participants were wearing Empatica E4 wristbands (

Figure 5) that measure skin parameters every second (Figure 6, Figure 6): measuring data from 3-axis acceleometer sensor in the range [-2g, 2g], data from photoplethysmograph (PPG), data from the electrodermal activity sensor in µS, Inter beat intervals. (intermittent output with 1/64 second resolution), data from temperature sensor expressed degrees on the Celsius (°C) scale.

Figure 5. Empatica E4 wristband

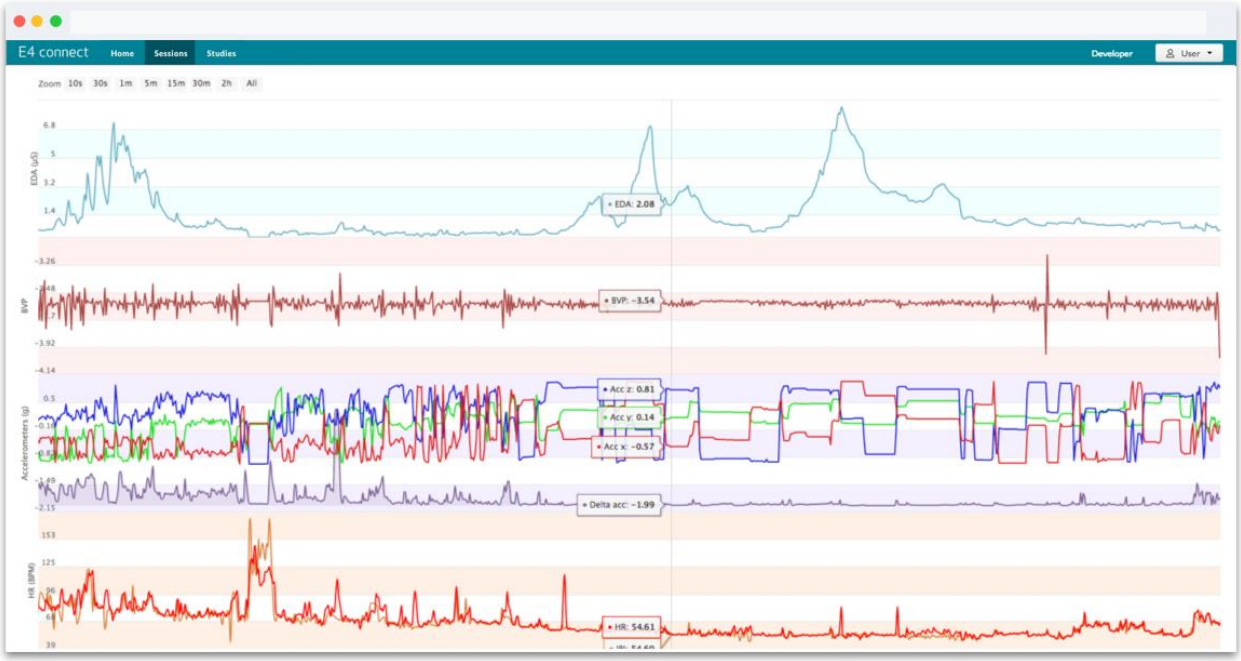

Figure 6.Example of multiple participants' visualization of physiological measurements (source Empatica)

This information was processed and introduced in a newly developed algorithm which helps detecting moments of stress (MOS) (Kyriakou, Resch et al. 2019). MOS relates to the SVG's by timestamp. Thus, the three main technologies can be connected through the timestamp information, so the information is merged in time and space. The data storage for these experiments is about 300GB.

3.2. Data preprocessing

As mentioned, each video file has embedded the GPS track. In order to extract it we are using a software developed in order to integrate information from Contour cameras. Figure 7 shows the software interface, practically after uploading the video you can download the GPS points as *.csv, *.kml, *.shp and *.gpx.

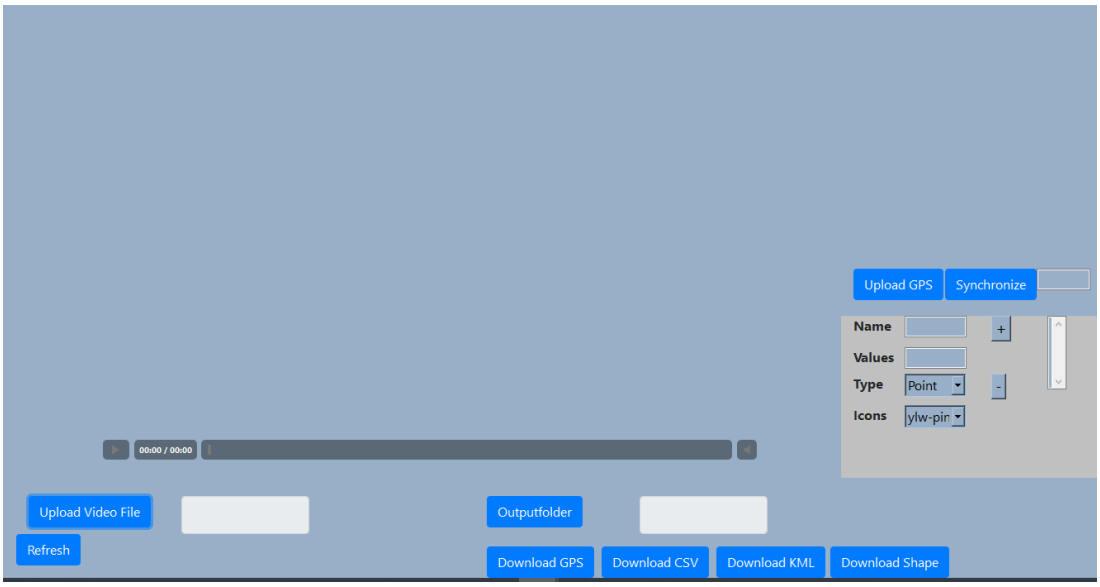

Figure 7. Camera player software – extracting GPS data

While in the last years a growing body of research started analyzing geonarratives, only recently specific software started to be build, such as Wordmapper (Ajayakumar, Curtis et al. 2019). This software is user friendly and intuitive, combining information from the GPS tract and transcribed interview (Figure 8). Contextual analysis can be followed on the narratives in this software. A great advantage lays in the possibility of exporting sentences with time and GPS information in commonly used formats such as ESRI shapefiles, Keyhole Markup Language (KML), and Comma Separated Values (CSV). For each one of the participants we had to clean the text transcripts of the audio files. They need to use a specific format for the time, i.e. [00:00:00] and to not include irrelevant words, e.g. "aaaa", "pffff". After cleaning, the transcripts and GPS point files were introduced one by one to be connected by time stamp in Wordmapper software. The field "folder" is requesting the location of the working files, field "narrative" the text document transcribed from the audio, and the field "GPS" needs the *.csv GPS point data. The field "Offset" is requesting the exact hour when the narrative starts according to the video time (e.g. if the geonarrative text starts at 00:00:10 as media time, we need to listen to the video and understand when the transcription starts, such as 14:00:00).

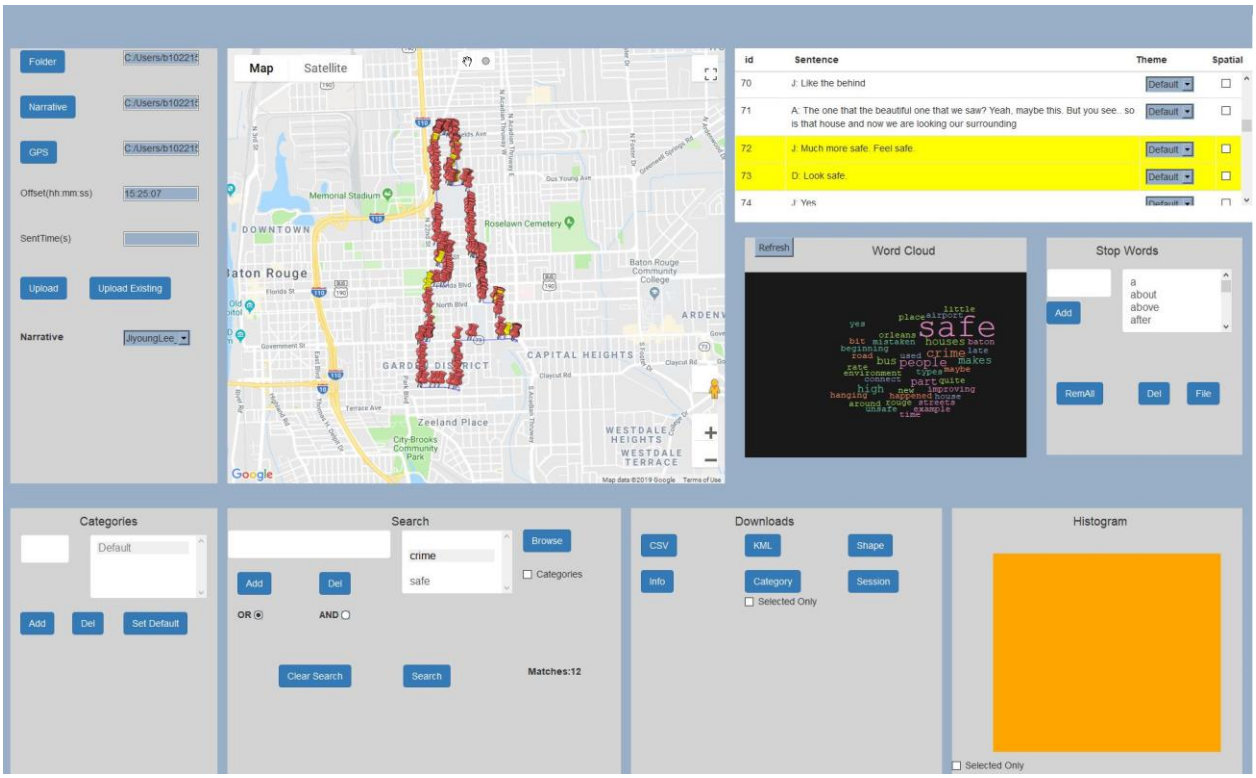

Figure 8. Wordmapper software interface – left side reading data; middle side showing the route with pins; right side displaying sentences, wordcloud and stop words; lower side for additional filtering

3.3. Methodology

3.3.1. Survey data

After cleaning the survey data, we design bar and pie charts in order to show participants' answers. This information serves as base of our study in order to understand how people feel in general in the city of Baton Rouge.

3.3.2. Spatial analysis

Timestamp is very important for connecting the different data sources. The audio files include only memory time, the biosensing wristbands include timestamp, while the videos include GPS location, timestamp UTC and memory time. Besides merging the field data, timestamp and location are also important for the additional data: crime data includes time and location, while other social, demographic and economic features do not include temporal info.

Kernel Density Estimation (KDE) is used to show crime, urban blight and moments of stress (MOS) density, all of them visualized through GIS-software. KDE is a non-parametric algorithm used to estimate the probability density function of a random variable (Botev, Grotowski et al. 2010). It is a

fundamental data smoothing. The KDE results depend on the selected parameters, such as the kernel function type, cell size, and bandwidth (Eck, Chainey et al. 2005). KDE is also used to visualize density of negative and positive polarities. Choropleth maps for two different spatial unit aggregation are used for crime occurrences. Various point symbols are designed for multiple layer representation.

3.3.3. Text analysis

Sentiment analysis is one of the most important applications of Natural Language Processing (NLP). It refers to the study of extraction of opinions and feelings from text. Generally, sentiment analysis tools rely on lists of words and/or phrases with positive and negative values. In the last years many dictionaries of positive and negative words were developed. For example, Liu and Hu opinion lexicon contains around 6800 positive and negative opinion words or sentiment words for English language (Hu and Liu 2004). Another example, AFINN, 2009-2011, is a human-labeled lexicon, containing a list of English words rated for valence with an integer between minus five (negative) and plus five (positive) (Nielsen 2011).

In the present study we are using Python package called Vader sentiment[4]. We are using the compound score, which is is computed by summing the valence scores of each word in the lexicon, adjusted according to the rules, and then normalized to be between -1 (most extreme negative) and +1 (most extreme positive). This metric is showing a normalized composite score measure of sentiment per sentence. Each lexicon-based sentiment analysis has limitations, and in the future work we will be testing multiple algorithms plus human-annotated data for comparison.

Other results from text analysis are represented by wordclouds and bar charts of most frequent words. These types of visualizations are important to show differences between various participants.

3.3.4. Detection of moments of stress (MOS)

Sensor-based emotion recognition can contribute to a better understanding of participants emotions, in this case the interest is towards stress emotions. Comparing the moments when participants are stressed with information from audio recordings and visual perception from videos can lead to better and increased understanding of people' feelings. There are multiple studies attempting to detects if a participant is stressed or not through various methodologies, their majority including machine learning elements. The algorithm developed by (Kyriakou, Resch et al. 2019) is a rule-based algorithm based on galvanic skin response and skin temperature, implemented in R programming. The rules were chosen instead of a machine learning algorithm due to the ability of integrating information from experts and of better understanding the processes (Kyriakou, Resch et al. 2019). This algorithm shows high accuracy during validation compared with other methods, reason why it is used for the present research. MOS are different for various age, gender, health condition and so on, and results are depicting some of these variabilities.

[4] https://github.com/cjhutto/vaderSentiment

4. Results and discussion

Criminal activities are well known as being high in the city of Baton Rouge. The southern part shows the lowest amount of crime, while the central and north area show high crime densities (Figure 9).

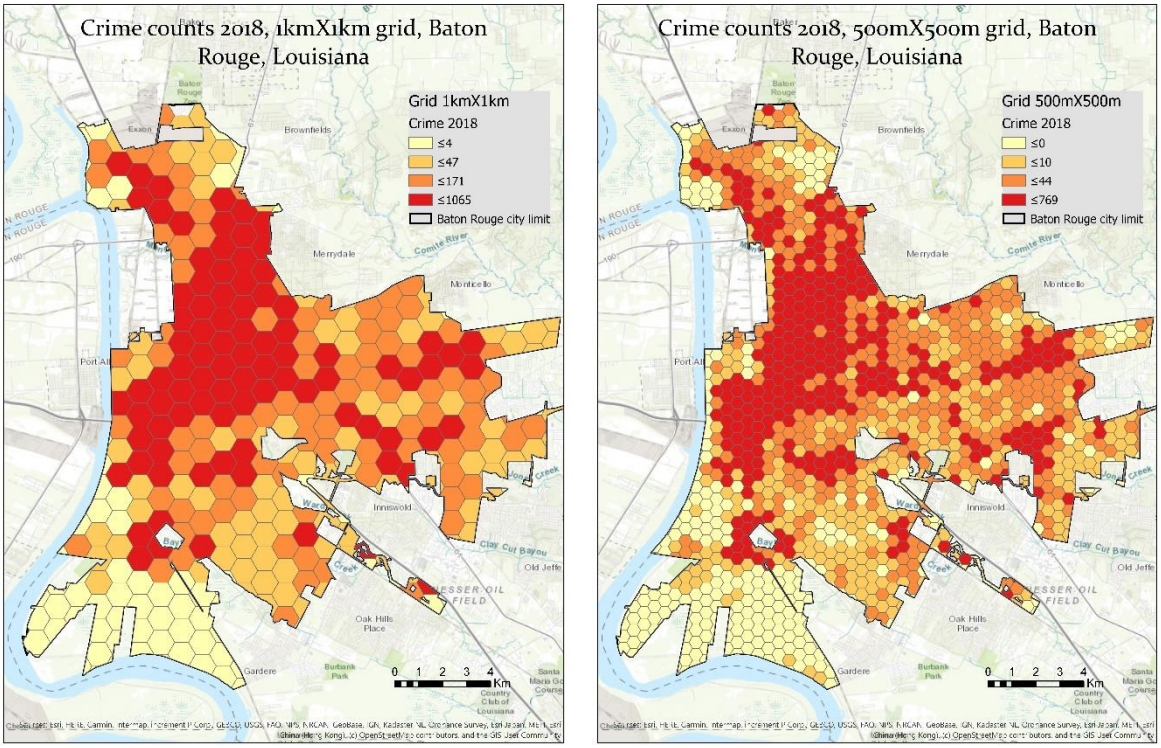

Figure 9. Crime counts in 2018, aggregated to 1km (left) and 500m (right) hexagons

As mentioned in the chapters above, this work included various steps:
(1) Firstly, we analyzed crime density in the city, after which we included 311 data. The 311 database includes a way to request services and report issues while on the go (e.g. issues about garbage, recycling, drainage, blighted properties). After working on the official data, we developed a short questionnaire as base for safety perception and influence of urban blight in peoples' perceptions.
(2) Secondly, we defined neighborhoods which we surveilled for extracting urban blight information through field work data acquisition. After having a clear picture of crime density and urban blight indicators extracted from the field work, we moved to the third pillar.
(3) We defined a route of ~30 minutes for collecting safety perception data from human subjects (see Figure 2 for the route).

Figure 10 shows that urban blight indicators extracted from the field work acquisition, based on literature and visual interpretation, are spatially different than the ones extracted from 311 data (Stratmann 2019). Thus, the present research brought finer definitions details which cannot be extracted from 311 data, representing calls for service (e.g. not everybody is calling to denounce a

bighted property, it depends on the neighbor's civic feeling). This analysis is not detailed in the present manuscript, where we are focusing on the third part of the complex study, namely on extracting safety perception information.

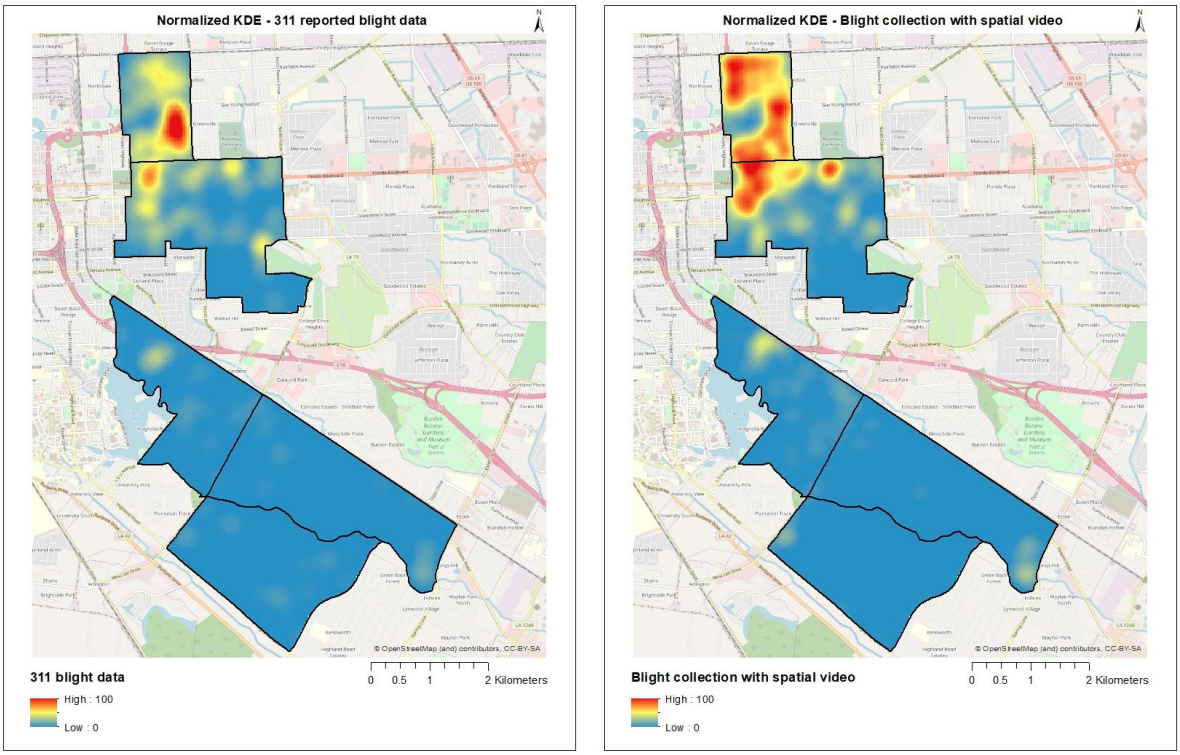

Figure 10. Urban blight from 311 data (left) and field data collection (right) source:(Stratmann 2019)

Preliminary results show variance in safety perceptions influenced, among others, by the familiarity with the area, gender, and professional qualifications. Next, hot spot analysis, spatial autocorrelation, and clustering methods will be carried out in the GIS environment together with text analytics (sentiment and topic modeling). In addition, moments of stress are extracted from the wristband measurements and compared with the video footage (image and location), and voice recording for the indicated timestamps.

We assume that a strong spatial relationship between crime and safety perception exists. Crime data and additional information are collected from official open data sources. Moreover, we consider place composition patterns in order to understand areas where participants feel safe or unsafe, and where crime occurrences happen.

This project shows relevance through using mixed geospatial design to improve the identification of crime-related variables and to explore perceived safety; collecting contextual information in a standardized way and in a format that can be archived; discussing possible improvements and enhancements of quality of life in Baton Rouge. It is important to understand the benefits and limitations of the techniques and the extraction of meaningful information. Results may be of interest

to law enforcement, environmental and sociological criminology, urban planning, and many other fields.

4.1. Survey

The survey had mainly four parts: residence information, safety perception, city and neighborhood, and general information. We received 44 questionnaires completed (i.e. we do not consider questionnaires which have missing information) from students (enrolled at LSU, Geography and Sociology Departments), from which 42 students live in Baton Rouge. Three are non-US citizens while 39 are US citizens. Regarding gender, 26 participants are females and 18 males.

For the question "Where do you feel less safe?" most respondents considered 6, 8 and 9. Also, 8 of them mentioned other places besides the indicated ones, such as campus, parking garages, bars, Tigerland, downtown areas, Alvin Dark, Uber, smoke store, bank. Shopping malls, movie theaters, nightclubs, bars, places that serve alcohol.

When the participants had to score the elements that influence their perception of crime from the from 1 (influences not at all) to 5 (influences most), the average results show the following scores (Figure 11): social media info 2.59, family and friends opinions 3.24, bad experiences in the city 3.49, types of people living in the city 3.41, crime hot spots 3.83. One participant mentioned other elements that influence most his perception, namely neighborhood landscape, economic development level, local schools' levels. Six of the 42 respondents were victims of crimes such as sexual assault, break-in apartment and car, and armed robbery. Studies of fear of crime assume that is primarily induced by direct or indirect contact with a criminal event. However, the results of the questionnaire show that only one of the six feels very unsafe in Baton Rouge.

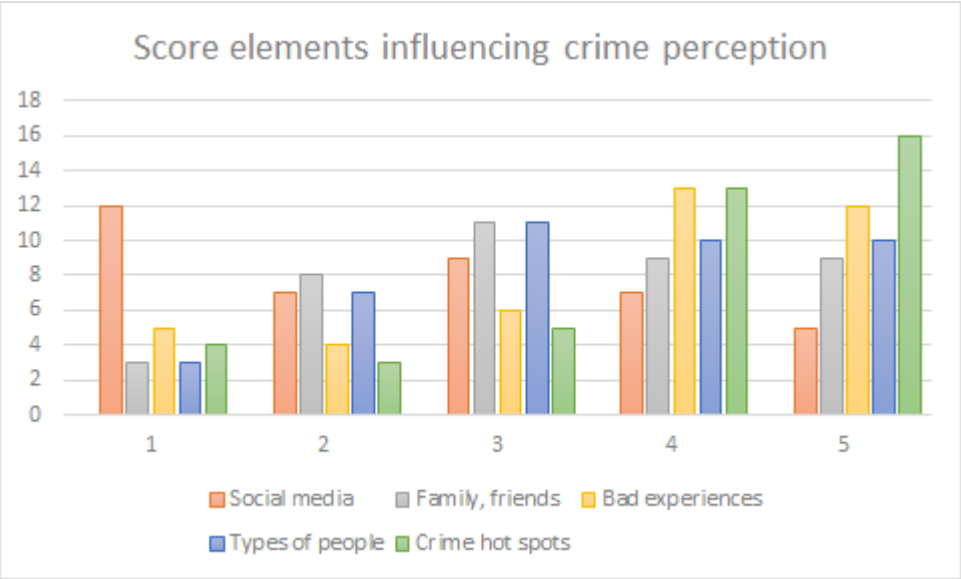

Figure 11. Elements influencing crime perception

Almost 30 respondents consider gas stations and alleys the most unsafe areas in the city (Figure 12). A large amount (66.1%) of the respondents are generally traveling in Baton Rouge by car (Figure 13). This is not surprising while considering the low development of bus stations and connections, the absence of bike paths and even of pedestrian paths. It is worth mentioning that Baton Rouge is the type of city spread out making it difficult to travel from point A to B without a car. While Baton Rouge is considered a high crime city, half of our respondents feel moderately safe in the city. Their safety perception is influence 83% moderately-high by urban blight conditions (Figure 13).

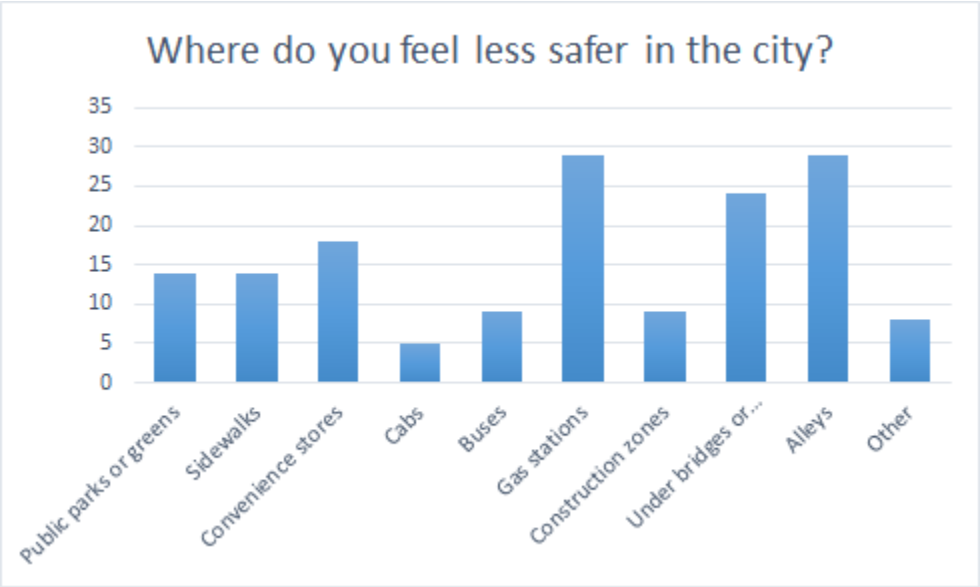

Figure 12. Places where people feel less safe in the city

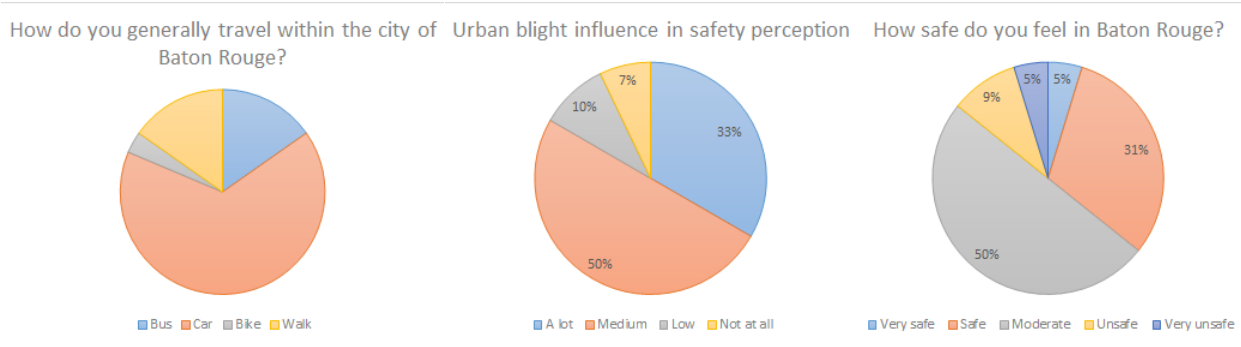

Figure 13. Travel ways (left), urban blight influence (middle), safety in Baton Rouge (right)

4.2. Geonarratives

Due to various limitations, the number of valid participants in the survey and in the geonarratives process is a little different. For the geonarrative study we selected a group of students, non-student locals, and non-student experts that almost coincide with the cohort completing the safety assessment

survey. In total, 46 people participated in the geonarrative study, where 32 people represented students (from Geography and Sociology department), 9 people represented local stakeholders, and 5 people were experts in the research field. The participants had different nationalities and ethnical backgrounds, and their majority held the US citizenship. In this manuscript we are presenting results of ten participants, all students, five males and five females.

Figure 2 (see above) shows the route that was selected for the geonarratives. We acknowledge that GPS errors can occur and sometimes due to road closures or other reasons the route had to be slightly changed (Figure 14). We drove on this route with each one of the 46 participants and we followed the same methods of acquisition and analysis for each one of them. We tried to drive the route at similar time of the day with similar weather conditions.

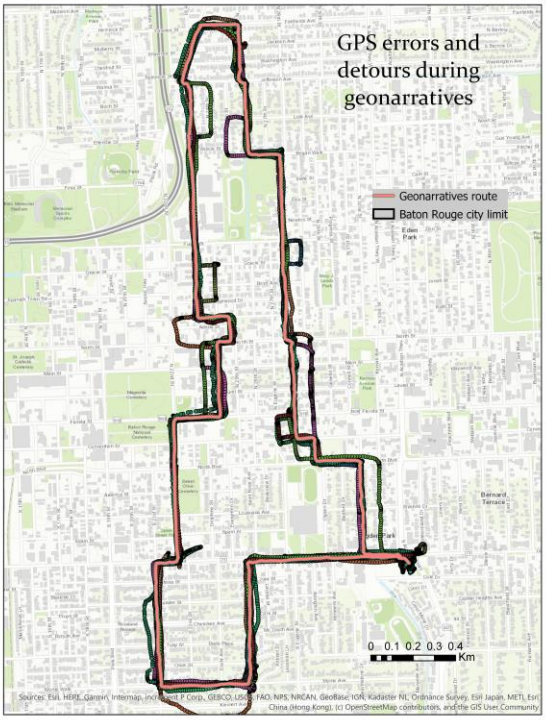

Figure 14. Overlay of the route for the ten participants

We extract GPS coordinates for each sentence per interview by using Wordmapper (Ajayakumar, Curtis et al. 2019), and then we upload them as format shapefile in ArcGis PRO. Figure 15 shows high crime densities all over the route surroundings, with small differences, while for urban blight we can notice the southern part with very low density and almost north where there are some empty spaces.

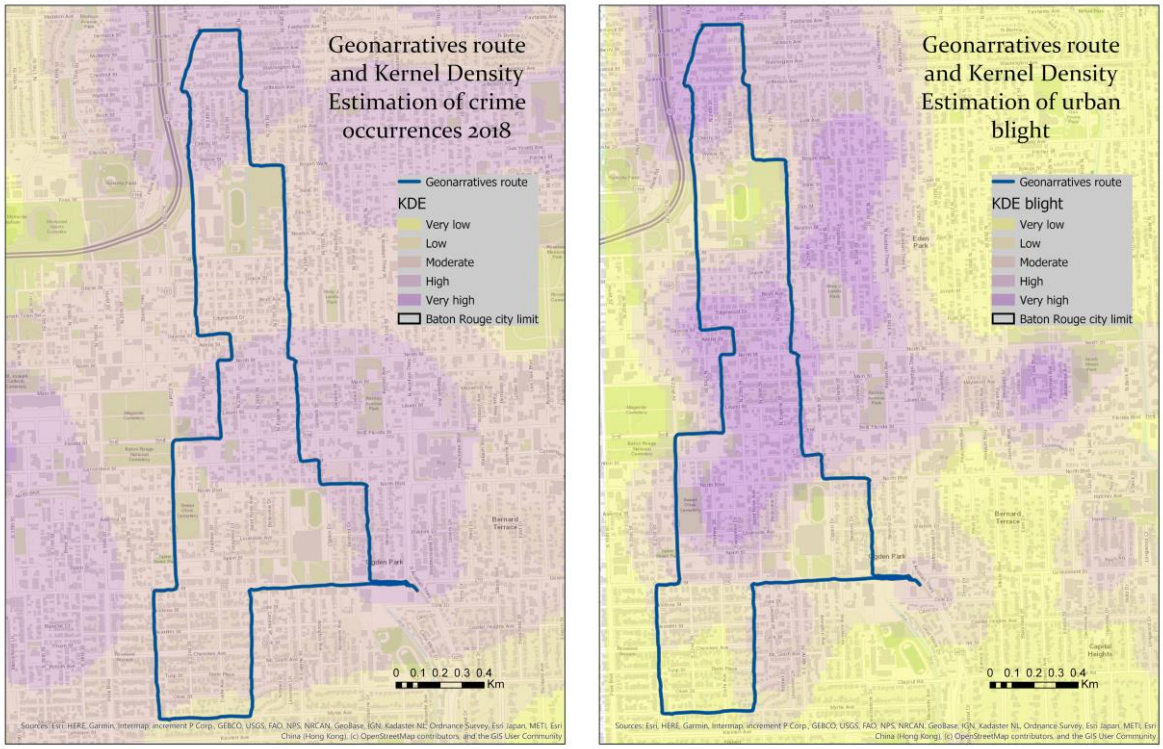

Figure 15. Geonarratives route overlays KDE of crime occurrences (left) and urban blight (right)

4.2.1. Sentiment analysis

We applied sentiment analysis models for each one of the ten participants' transcripts. Figure 16 shows that the density hot areas are stronger defined for positive sentences than for the negative ones. While driving up north high density of negative polarity tend to occur, while descending from the northern part is the reverse: no negative polarity for high or very high-density areas. In comparison, positive messages tend to get denser no matter the direction (up north or down south).

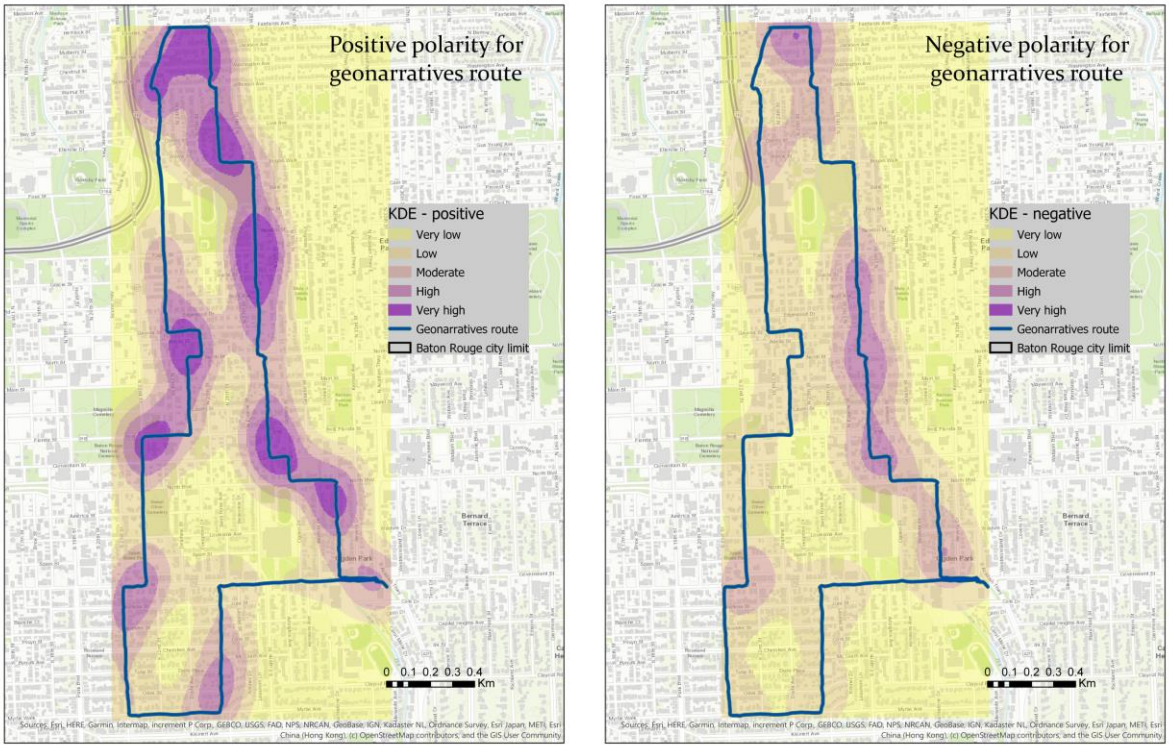

Figure 16. Geonarratives route overlays KDE of positive polarity (left) and negative polarity (right)

We expected more negative polarity than positive from the text analysis. Results can be different by using another sentiment analysis algorithm or by considering human annotators. One explanation for the present case may be related to the route selection: the respondent may be more negative in the first part of the route when expecting to cross unknown areas and more positive in the second part after realizing that the route is not moving towards higher (objective) crime areas.

There are many mixed sentiments during the interview for which we are planning on creating categories or applying topic modeling as future work. In the following rows will be presented parts of the interviews [A is the respondent and Q is the interviewer]:

A: I am noticing quite a few houses have bars in front of the windows. Q: Do you think that is to deter property crime? A: Oh, absolutely, absolutely....and possible bodily crime too, depending on the inhabitant, but the main reason would be for property crime, for this time of the day, when people are not at home.
Q: What are indicators that makes you say it's a poorer area? A: The way the houses are. There's a lot of trash in the front and old furniture. A: If there were more people around, I would probably feel safer.
Q: How do you like this neighborhood? Is it different? A: A little bit. It just seems like people are more aware of their surroundings and keeping their lawns and cars and everything together and nice.
Q: You never use the public transportation? A: No. [the most common answer]

Q: I see that everybody has cars at these houses, even though they do not look so nice. A: Another thing I've noticed is people parking in their yard, even when there's a driveway.
A: I think the assumption is in "nicer areas" you're at less of a risk of crime. Q: Yes, that is the assumption. A: But unless there's a neighborhood watch, we could easily park in front of a house, break into in, and be out in 5 minutes, if not less. That why I say there's an "illusion of safety" for people here.

As abovementioned, sentences can be visualized on the map (Figure 17). Each sentence includes GPS coordinates, time stamp and sentiment value. For example, the sentence "I would never walk here alone" is classified as negative, same for "Yeah, if I am alone I feel kind of uneasy about it", whereas "The houses are much bigger and there is no trash in the front yards. Everything is nice. They obviously take care of their house" is showing a clear positive polarity.

The feelings expressed in these sentences are common for most of the participants: during the drive, in the northern part of Government street, participants were discussing about not well-maintained houses and gardens, abandoned houses, trash, and many other signs of urban blight. When moving to the south of Government street, in the Garden district, participants considered it clean and with a nice environment. In the same time, all the participants discussed the clear income gap between the two parts (north and south Government), which are so close in space.

Figure 17. Mapping transcription and sentiments

Interestingly, one of the participants has been victim of a crime multiple times, but he was not afraid or uncomfortable to discuss about it (Figure 18). He is mentioning the idea of "illusion of safety" – when you feel safe while being under crime risk. As example, his car was broken in a "nice area", showing that various crime types can occur no matter how good looking or clean is a specific area, neither if people having high income and education live there. This information supports a controversary body of research, arguing that previous victimization might make a person avoid areas and people, thereby reducing their fear of crime (McGarrell, Giacomazzi et al. 1997, Katz, Webb et al. 2003).

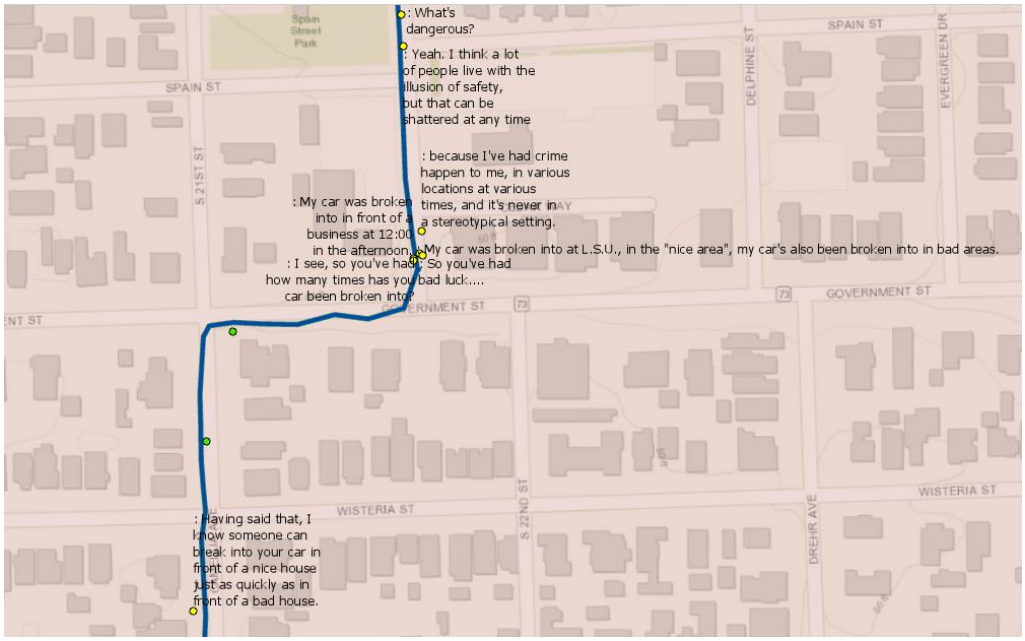

Figure 18. View of one participant about crime

4.2.2. Wordclouds

Wordclouds or text clouds are a way of visualizing text data. The higher the frequency of a specific term determines the higher size of the term in the cloud (Figure 19 and Figure 20). While using the key term "crime" one of the respondents is bringing into discussion terms of "money", "cause" and "crime rate". The respondents frequently refer to the concept of neighborhood and their understanding about the areas throughout the route. The two main categories in the wordclouds include "safe" and "unsafe" terms. Among others, people's perception about safety connects to food outlets and stores, one of the participants mentioning that more industrial looking outlets make him feel uncomfortable.

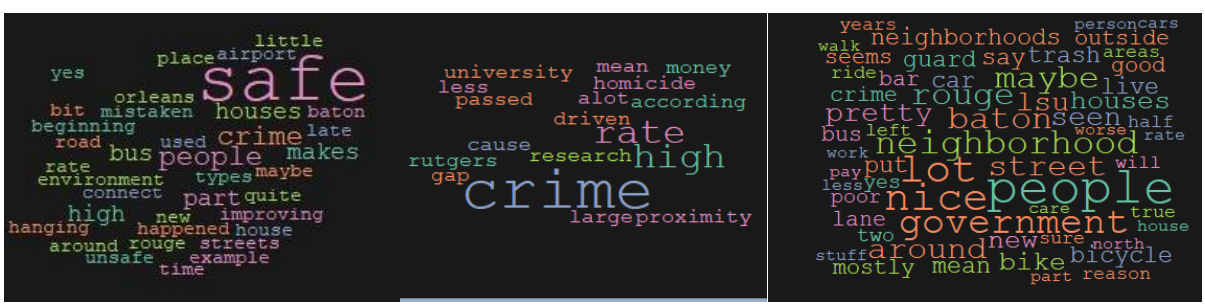

Figure 19. Wordclouds made in Wordmapper (left and middle side include the search terms "crime" and "safety"; right side includes all the narrative of one participant

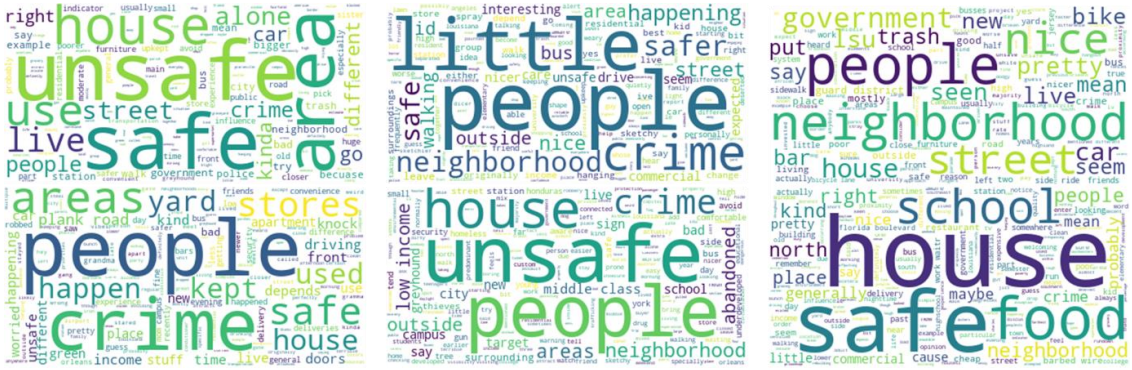

Figure 20. Wordclouds (created in Python) for each participant while carefully selecting additional stop words

Figure 21 is an example of top 25 most common used words by one participant. It represents the same information as the wordcloud, but in the graph form. We notice that the participant is discussing about low-middle income houses and the most common word used is "unsafe". Background literature shows relationships between economic situation and crime occurrences, whereas through this interview we find also the crime perception being connected with income. The respondent is not using strong crime related words; however, it is mentioning negative aspects about abandoned buildings and unsafe surroundings.

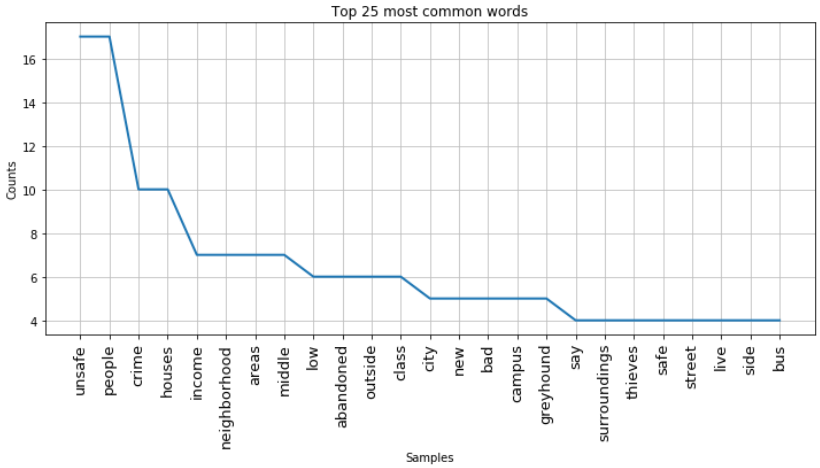

Figure 21. Top 25 most common used word during the interview

4.3. Moments of Stress (MOS)

MOS are identified in order to be connected, if possible, with contextual information from the participants. Figure 22 shows an overlap of MOS of the ten participants. It is not visually clear which participant is which, however the purpose of this visualization is to realize how dense the points distribution is over the route and to show where are the more spatial overlaps. It is surprising that the intersections are positively related with the MOS detection. This fact needs careful interpretation and more in-depth analysis. It is important to mention that the algorithm for detecting MOS was tested for walking and biking, and not for car driving (Kyriakou, Resch et al. 2019). Researchers discuss the

influence of stress on design in-car enhancements and on driving maneuvers (Matthews and Desmond 1995, Hill, Boyle et al. 2007), which may be relevant in the present research: the participant (always sitting on the driver's right side) does not trust the driver's ability of safe driving and this is heightened in intersections.

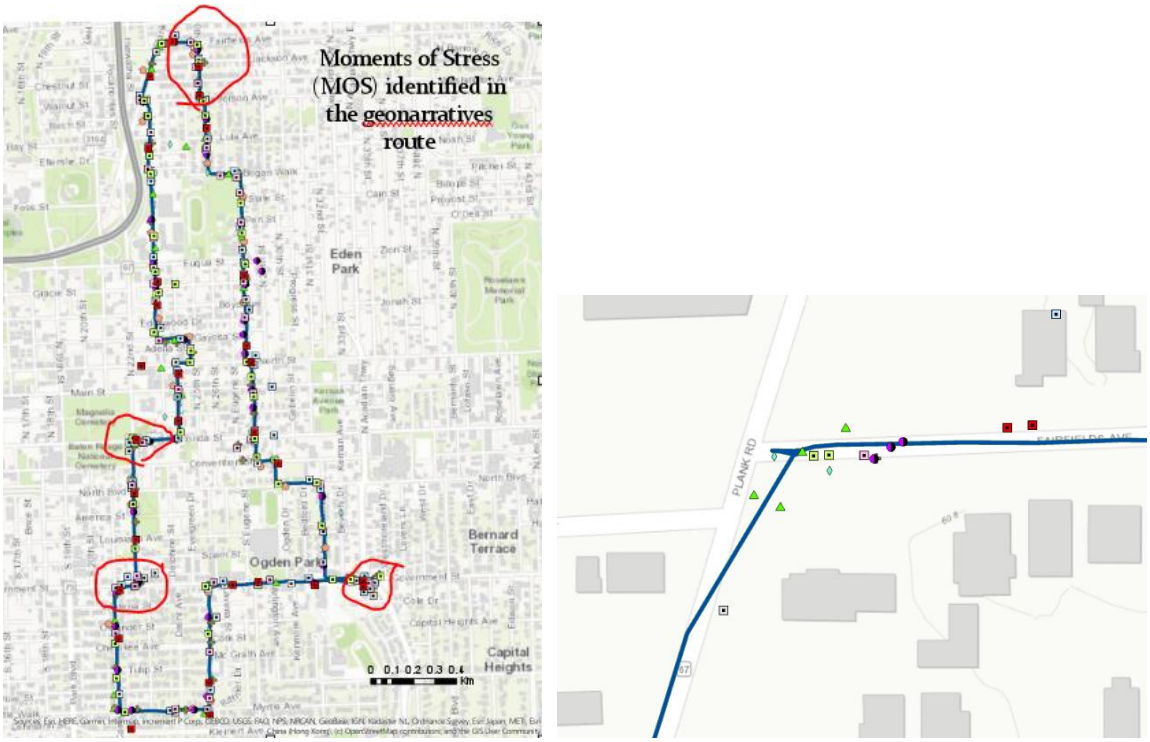

Figure 22. Points of MOS over the geonarratives route

Figure 23 shows differences between male and female stressful moments. During the interview males articulated that they do not feel highly unsafe during the geonarratives route, while females seemed to be more uncomfortable with the situation. However, the MOS analysis shows higher density of MOS for male participants, mostly around intersections and in the center part of North 28 street. These are preliminary results and we will detail the analysis in order to understand why intersections are showing multiple moments of stress (e.g. using KDE can be misleading and a hotspot analysis such as Gi* may be more appropriate; participants can suffer of transportation anxiety involving dystychiphobia (irrational fear of accidents) or amaxophobia (irrational fear of riding) (Bennett, Vijaygopal et al. 2019)). Overlapping the MOS from a random participant over a KDE of MOS for all participants shows that the participant is highly correlated with the total trend, however some specificities are resulting from other participants. Thus, participants' opinions vary during the route and the context presented by the respondent has different values for their interior stress. There are various stressors which can impact the participants differently according to gender or age.

Figure 24 shows an overlap between one participant's MOS and KDE of sentiments. As abovementioned, we notice moments of stress at intersections. Thus, even though we have positive

or negative polarity, MOS are occurring in multiple locations. Another density estimation can be used for comparing the results and understand behaviors at finer scale – can be followed as future work.

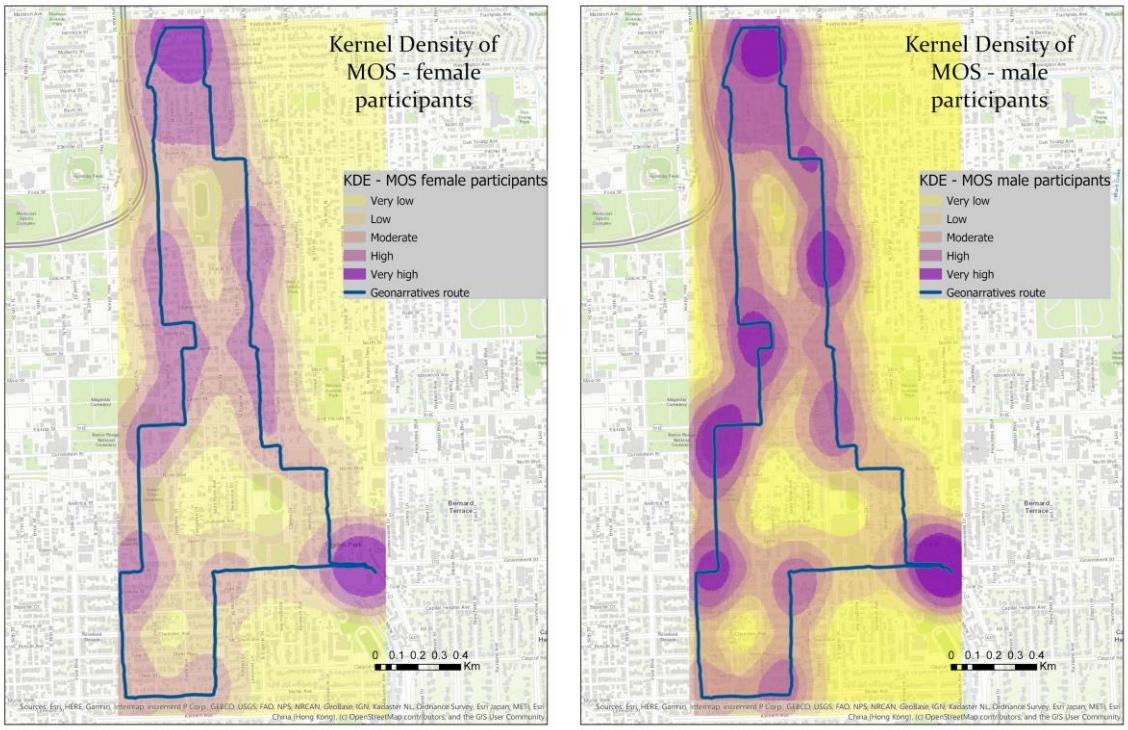

Figure 23. Differences between male and females MOS density

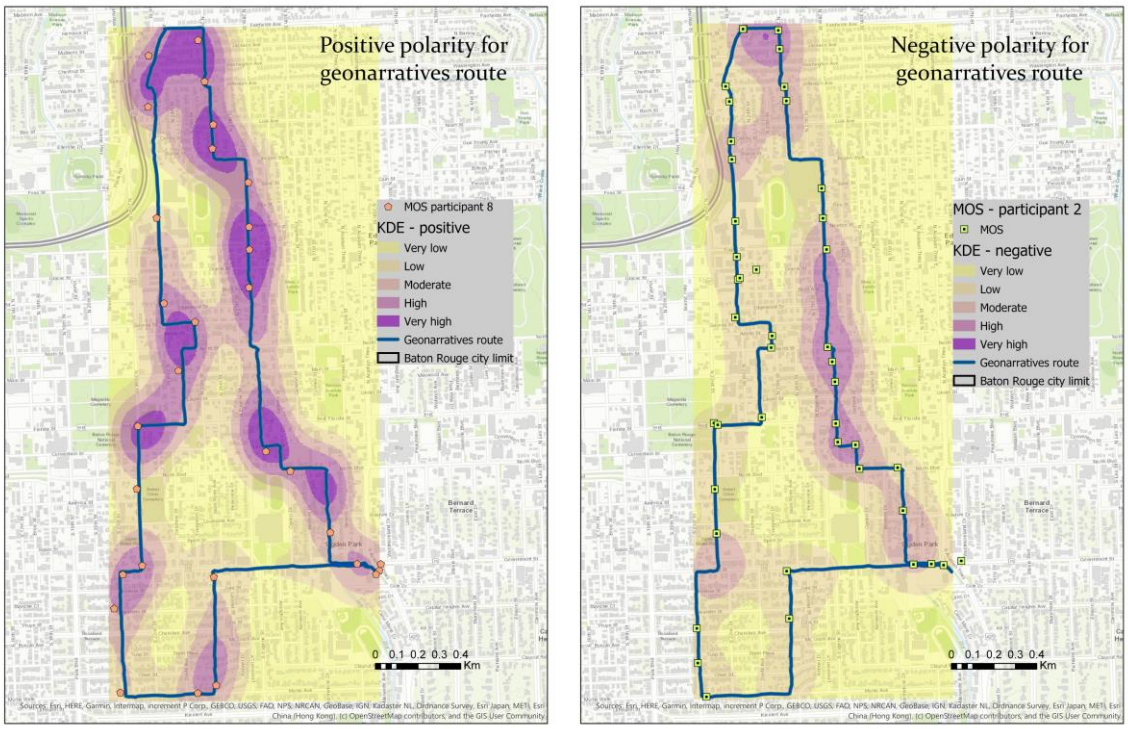

Figure 24. Geonarratives route overlays KDE of positive polarity (left) and negative polarity (right) and MOS for one participant

For each interview we have a video-audio-physiological entry in the database. After detecting MOS, we extracted screenshots from the videos for each participant at the MOS time (Figure 25). There is no immediate explanation from the videos for the detected MOS, although many of them are detected when the car approaches the "Stop" sign for the intersection. Another example is when another car passes by the interview car or when a cyclist is approaching. An interesting step would include the data acquisition by walking instead of driving – however, this is a difficult task due to the locations surveilled. In addition, we asked our participants during the interview their opinion on stopping the car and walking for a short distance and we received a refusal most of the times, some of the participants even feeling extremely uncomfortable with this idea. Thus, walking experiments may be hard to follow and hard to find participants.

One of the next steps includes comparison of MOS locations, sentiment value and contextual information from the interview's transcripts. However, there is need of complementary analysis on other tools of text analysis (other sentiment algorithms, topic modeling etc.).

Figure 25. Examples of MOS from spatial video

5. Conclusion and future work

Following mixed methods approaches started to be increasingly adopted in geoinformatics or geospatial related work. This research builds upon this stream and it is testing the compatibility of data collection and analysis through different technologies, describing a mixed qualitative and quantitative analysis. In this work we extract perceived safety information from the data acquired using mixed methods and we implement it in a GIS-based model for context analysis. The mixed techniques include a short survey, spatial video and spatial interviews on the field with study participants, and the extraction of moments of stress from biosensing wristbands. While comparing official crime data reported to the police, urban blight indicators and people's perceived safety, extracted from the mixed-method approach, we notice spatial overlaps, but not completely masking each other.

Generally, our participants felt more cautious with a degree of unsafety while driving the first part of the route, and less cautious in the second part. However, same space gives different perspectives. Some of the elements which participants mentioned as important in their perception include familiarity with the area, having heard bad stories about the area, knowing crime statistics, having bad experiences on the field, or simply being the victim of a crime elsewhere.

Another remark would be that people tend to talk about various areas in the city while driving the route and they like to emphasize their own stories. This is contextually relevant; however, it deviates from a spatiotemporal analysis and it cannot be interpreted quantitatively. Participants engage differently in the discussions according to their interest (e.g. one of the participants used to live in one of the surveilled areas and she provided interesting information contrasting respondents who never visited the locations). This research shows that urban blight indicators have a role in respondents' perceptions, some of them not thinking about it before the interviews. In the same time, we found several participants worried for the organization of the neighborhoods. This leads us to believe that a larger effort to work near the urban decay is needed to help improve these neighborhoods. High poverty rates, low education level and lack of economic opportunity are the main elements which, when improved, will change the quality of life and environment. Nevertheless, for all these components new policies, politics and so on need to be discussed.

As a follow up to the plethora of research papers on fear of crime or crime safety perception, our findings show differences between males and females, together with the age variability (Snedker 2015). The density map for MOS shows high peaks on street junctions, result which should be investigated further. In the meantime, around MOS there are areas of positive sentiments extracted using Vader algorithm. This is a common outcome of sentiment analysis, namely positive and neutral feelings tend to be easier to detect than negative ones. Thus, additional sentiment analysis can be used and compared with human annotators' results. In addition, topic modeling through Latent Dirichlet Allocation may be a good starting point in extracting "safety" or "crime-related" topics from geonarratives.

In Baton Rouge there is a street (or two) which represents a barrier or border in people's perception between a rich and a poor neighborhood. There are historical and sociological explanations about the implications brought by this barrier which will be considered in a further manuscript. Some participants consider Government street a border, while others discuss about Florida street. Gentrification processes take place between the two streets which might bring different perceptions in time. Researchers show that perceived safety has relationships with the changes taking place in the neighborhoods (Lewis 2017), thus the post (present) and after-gentrification analysis may bring new insides on what people consider fear attractors or generators.

Limitations that can occur while using the mixed technologies include weather conditions, sunlight, time of the day/night; closed streets, elements obscuring the view, e.g. parked cars, bad positioning

of the devices, low volume on the audio recording + additional noise, battery performance; specific start and end time (different devices and thresholds), GPS signal deficiencies in some areas.

In order to extract safety features from the fusion of methods, it is important to understand spatial crime distribution in the urban area. The knowledge of crime prevention and perception draw attention in the recent years to urban planners, another field where the proposed project touches ground. Thus, it would be relevant for the future work to include in the project urban planners, sociologists, psychologists and other related fields. Moreover, the experimental results showed in this report would benefit of the possibility of automatic data extraction and analysis. Now we are proposing a mixed method approach which later can be considered in an automatic spatiotemporal workflow.

By monitoring crime perception and crime occurrences over time, a temporal analysis can help finding similar and dissimilar trajectories. This can be an important part for example while applying crime prevention strategies. Further integration of the results in spatial crime forecasting can be done for larger areas. Another important step refers to collaborations with city officials to better understand subjective crime and its connection with crime occurrences.

Furthermore, the highly relevance for multiple area testing is included in the interdisciplinary context of the project. Besides the crime status, some of the reasons why this research project was carried out in the US at the Louisiana State University in Baton Rouge are: the position of my major supervisor, Professor Michael Leitner, and the availability of the devices needed in the project, bought by himself from several funding or borrowed through collaborations (such as the wristbands for skin measurements, from Associate Professor Bernd Resch, my second supervisor from the University of Salzburg). In addition, crime information and other additional data is easier to collect in the USA than in Europe. After controlling and evaluating the analysis in Baton Rouge, same techniques may be applied in Austria.

Acknowledgements

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Appendix 1. Background questionnaire

Background questionnaire - Safety Perception in the city of Baton Rouge

Thank you for participating in our research about **safety perception**. The research focuses on the perception of crime in Baton Rouge and on assessing urban blight and its relationship with criminal activities.

Your contribution is highly appreciated, and your answers will be kept strictly confidential.

This survey consists of two parts, (1) filling out a brief questionnaire and (2) a short mapping exercise.

Thank you for taking part and helping with our research. We really appreciate your time and effort! Please, answer ALL questions! There are no right or wrong answers, all responses are truly helpful to us.

It takes about 3-5 minutes to complete this survey.

1) Assessment Background Questionnaire

Please answer the following questions:

a) Residence Information

Currently living in Baton Rouge? ☐ yes ☐ no

If yes, please mention where you live: Click or tap here to enter text. (please provide your residential address or your neighborhood information)

If yes, since when have you lived in Baton Rouge? Click or tap here to enter text.

How do you generally travel within the city of Baton Rouge? (please check more than one box, if needed)

☐ bus

☐ car

☐ bike

☐ walk

☐ other: Click or tap here to enter text.

b) Safety Perception

How safe do you feel in Baton Rouge, in general?

☐ very safe

☐ safe

☐ moderate

☐ unsafe

☐ very unsafe

Where do you feel less safer in the city? (please check more than one box, if needed)

☐ Public parks or greens

☐ Sidewalks

☐ Convenience stores

☐ Cabs

☐ Buses

☐ Gas stations

☐ Construction zones

☐ Under bridges or underpasses

☐ Alleys

☐ Other: Click or tap here to enter text.

Score the elements that influence your perception of crime from the list below from 1 (influences me not at all) to 5 (influences me most).

Click or tap here to enter text. Social media info

Click or tap here to enter text. Family and friends opinions

Click or tap here to enter text. Bad experiences in the city

Click or tap here to enter text. Types of people living in the city

Click or tap here to enter text. Crime hot spots

Click or tap here to enter text. Other: Click or tap here to enter text.

When do you feel unsafe? (please check more than one box, if needed)

☐ morning (7 am to 12 noon)

☐ afternoon (12 noon to 5 pm)

☐ evening (5 pm to 8 pm)

☐ night (8 pm to 7 am)

☐ never

Why do you think Baton Rouge is dangerous? (please check more than one box, if needed)

☐ It is a poor area.

☐ My family and friends think it is dangerous and they influence me.

☐ I am familiar with crime data and know the crime statistics.

☐ It has a lot of homeless people.

☐ People who live in Baton Rouge say it is dangerous.

☐ I had some bad experiences in the city.

☐ The ethnicity of the people living in the city.

☐ Other: Click or tap here to enter text.

Are there specific places (public or private ones) you avoid due to safety concerns? ☐ yes ☐ no

If yes, please specify these places: Click or tap here to enter text.

Have you been a victim of a crime in Baton Rouge? ☐ yes ☐ no

If yes, please specify in more detail: Click or tap here to enter text.

How does **urban blight** influence your perception of safety?

(**Urban blight** describes disordered neighborhoods characterized by abandoned buildings, broken windows, high-grown vegetation etc.)

☐ a lot – I feel much less safe in these areas

☐ medium – I feel less safe in these areas

☐ low – I almost feel the same way as in areas with little to no urban blight

☐ not at all – I don't feel any difference compared to areas with little to now urban blight

c) City and neighborhood

Enter your perceived score from 1 to 5 for each one of the following attributes for the **entire city** of Baton Rouge, where 1 means "not at all" and 5 means "completely":

The city is safe	☐1	☐ 2	☐ 3	☐ 4	☐5
The city is wealthy	☐1	☐ 2	☐ 3	☐ 4	☐5
The city is beautiful	☐1	☐ 2	☐ 3	☐ 4	☐5
The city is boring	☐1	☐ 2	☐ 3	☐ 4	☐5

The city is livable	☐1	☐ 2	☐ 3	☐ 4	☐5
The city is walkable	☐1	☐ 2	☐ 3	☐ 4	☐5
The city is cycling friendly	☐1	☐ 2	☐ 3	☐ 4	☐5
The city has good public transport	☐1	☐ 2	☐ 3	☐ 4	☐5
The city is depressing	☐1	☐ 2	☐ 3	☐ 4	☐5

Enter your perceived score from 1 to 5 to each one of the following attributes for **your neighborhood/residential address** of Baton Rouge, where 1 means "not at all" and 5 means "completely":

My neighborhood is safe	☐1	☐ 2	☐ 3	☐ 4	☐5
My neighborhood is wealthy	☐1	☐ 2	☐ 3	☐ 4	☐5
My neighborhood is beautiful	☐1	☐ 2	☐ 3	☐ 4	☐5
My neighborhood is boring	☐1	☐ 2	☐ 3	☐ 4	☐5
My neighborhood is livable	☐1	☐ 2	☐ 3	☐ 4	☐5
My neighborhood is walkable	☐1	☐ 2	☐ 3	☐ 4	☐5
My neighborhood is cycling friendly	☐1	☐ 2	☐ 3	☐ 4	☐5
My neighborhood has good public transport	☐1	☐ 2	☐ 3	☐ 4	☐5
My neighborhood is depressing	☐1	☐ 2	☐ 3	☐ 4	☐5

d) General Information

Gender: ☐ male ☐ female

Age: Click or tap here to enter text. years

Nationality: ☐ US citizen ☐ non US citizen

Student: ☐ yes ☐ no

If no, what is your profession? Click or tap here to enter text.