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Enriching geospatial data with computer vision to identify urban environment determinants of social interactions

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Abstract. Characteristics of urban space (co-)determine human behaviour, including their social interaction patterns. However, despite numerous studies that have examined how the urban space impacts social interactions, their relationships are still poorly understood. Recent developments in computer vision and machine learning fields offer promising new ways to analyse and collect data on social interactions. This study proposes a new computer vision-based approach to study how the urban space impacts social interactions. The proposed method uses pre-trained object detection models to detect social interactions (including their geo-locations) from street-view imagery. After that, it regresses urban space characteristics –which are also detected using object detection models – on social interactions. For this study, 294,852 street-level images from three Dutch cities are analysed. Results from linear regression analysis show that for these three Dutch cities people tend to meet in places with a strong presence of recreational attractions and bicycles. Also, the results of data collection and image processing can be used to identify the areas most likely to produce social interactions in urban space to conduct urban studies.

Keywords. social interaction, object recognition, urban design, computer vision

1 Introduction

Characteristics of the urban space define the patterns of how people socially interact with others in cities. Social interaction – defined as reciprocal stimulation among individuals – is a complex behaviour where cities' appearance, amenities, and form have significant impacts (Lebel et al., 2012). Urban space concerns all city spaces between buildings in the open air (Krier & Rowe, 1979). It can be described using a variety of variables, including the road network, traffic volumes, street furniture, land uses, etc. For instance, it is expected that interactions between people tend to take place in locations with better walking accessibility (Sheng et al., 2021; Abass & Tucker, 2021), greenery neighbourhoods (Abass & Tucker, 2016; Krellenberg et al., 2014), places with slow-moving traffic or limited parking (Uslu et al., 2010), and neighbourhoods with a shorter distance to the city centre, mixed land-uses, and higher densities (Mouratidis, 2018). These hypothesised relations imply that specific characteristics of the urban space are more likely to promote social interactions between individuals than others.

A thorough understanding of the relationships and dynamics between urban space and social interactions is essential for society. The COVID-19 pandemic has reduced the possibilities for face-to-face interaction between individuals. This has highlighted the harmful effects of the lack of it on people's well-being, which has increased cases of mental disorders, suicides, domestic violence, and disease-related deaths (Holt-Lunstad, 2021). By reshaping the urban space, policymakers and urban planners could stimulate the number of social interactions and decrease the undue adverse effects caused by the lack thereof. A deep understanding of this relationship will help policymakers to consider the impacts of urban-related projects on social interactions and prioritise or define projects positively impacting this social behaviour.

The relationship between urban space characteristics and social interactions is still poorly understood. While a considerable body of research is devoted to identifying the effects of social factors on social interactions, only a few studies have considered the impact of urban space on human interactions (Abass et al., 2020). Moreover, contradicting findings are reported. For instance, while some studies claim that higher density areas cause social problems such as a lack of a sense of safety and fewer social interactions (Soltani et al., 2019), other reports evidence pointing in the opposite direction (Mouratidis, 2018). The small number of studies and the sometimes contradictory results may be partly explained by the difficulty of collecting high-quality data on social interactions. The state of practice in social interaction data collection is based on questionnaires (Sugiyama & Thompson, 2006), surveys (Abass and Tucker, 2021), field observations (Lipovská et al., 2013) and other paper-diary methods (Mossong et al., 2008). These practices are often slow, inaccurate, expensive, or intrusive. Consequently, data on social interactions are scarce – hindering studying the phenomenon (McCall, 2015).

Recent development in machine learning and computer vision offer promising ways to analyse and collect urban and social interaction data. Several computer vision studies have developed models to infer social interactions based on so-called F-formations (Zhang & Hung, 2016;). Additionally, object recognition models have been developed that can accurately detect objects, such as buildings, amenities, and vehicles in images (Howard, 2019). These developments in computer vision, combined with the widespread availability of geo-tagged images (e.g., from Google street-view), enable creating high-resolution datasets of social interaction and studying social interaction in more profound ways.

The objective of this study is twofold. The substantive aim is to deepen understanding of the relationship between the urban space and the places where people have social interactions. The methodological aim is to develop a computer-vision-based method to analyse the areas most likely to produce social interactions in urban space. This study ultimately aims to enable planners to design more liveable cities that promote social interactions.

2 Methodology

2.1 Data and software availability

This study uses street-level images and geographic information from Google and Open Street Map (OSM). The data are collected per city and obtained within their administrative boundaries. Images come from Google Street View (GSV) by querying for different coordinates. Each GSV image corresponds to a 360-degree panorama view from which four independent images of 90-degrees-view are obtained. In addition, for each image, the date when the picture was taken (month and year) and its exact coordinates are stored. The Geographic Information System (GIS) data are composed of urban-related concepts such as network topology, locations of different shops or facilities, or polygons of parks, and are retrieved from OSM. A program was developed in Python using GeoPandas and was executed using a Core i5 8GB ram Linux Mint machine.

2.2 Social interaction and object detection using computer vision

GSV images are analysed to identify people as well as urban-related factors. This study uses the number of people as a proxy for the frequency of social interactions. Therefore, the GSV images are processed with an object recognition model – a machine learning method used to recognise objects in images – for people identification. More specifically, we use SSDMobileNetV3 (Howard, 2019). Finally, since each image is geo-located, the propensity of social interactions can be mapped. In addition, the GSV images are exploited to identify urban-related variables and characteristics to complement the GIS data collected from OSM. We extract from the images the presence of vehicles, bikes, etc.; urban amenities, such as bus stops, benches, bike racks, children's playgrounds, etc.; and land use, such as offices, shops, residential zones, etc. To do so, we use the same object-recognition model as we used to identify people.

2.3 Establish relations between social interactions and urban-related data

This study applies linear regression to identify relationships between the number and locations of social interactions (*i.e.*, number and location of people) and transport factors. Social interaction is the dependent variable, and all urban-related variables (*e.g.*, network topology, presence of vehicles, bus stops, benches, or shops) are the independent ones. Next, we apply a spatial auto-correlation model. This model allows studying the spatial relationships between the locations of, *e.g.*, vehicles and social interactions. Both approaches aim at identifying what urban variables and characteristics correlate with the location of social interactions.

3 Results

3.1 Data collection

We analyzed GSV images and collected GIS data for three cities in the Netherlands: Delft, Gouda, and Katwijk. We retrieved 294,852 street-level images for the years 2015 to 2021. In addition, the traffic network and data of some amenities such as the location of restaurants, schools, or pubs are obtained from OSM. For illustration, Fig. 1

shows the location of the images collected in red dots, the amenities in dark stars and the underlying traffic network for Gouda.

Figure 1. Data collected for the city of Gouda, the Netherlands. Red dots are the location of GSV images, dark stars indicate amenities such as restaurants, libraries, bars, schools, etc., and the lines correspond to the traffic network.

3.2 Street view imagery process

We illustrate the results of the image processing approach for the city centre of Delft, see Fig. 2. The left-hand side map shows the number of people per hexagon; the right-hand side map shows the number of vehicles per hexagon. To create these maps, 8,840 street-level images from 2018 are used. Using SSDMobileNetV3, we identify and count the number of people and private vehicles. Finally, we aggregate the counts to 30 meter-side hexagons.

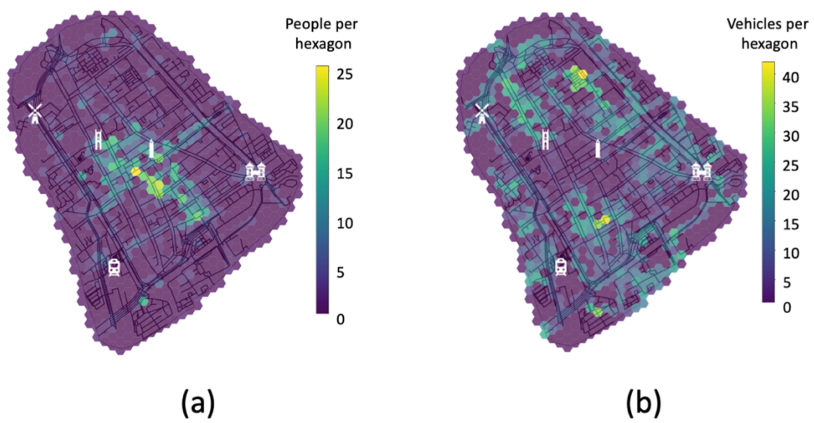

Figure 2. (a) People presence and (b) vehicle counts in the city centre of Delft. 8,840 street-level images from Google Street View were collected, and data is aggregated in 30-meter-side hexagons.

3.3 Establish relations between social interactions and urban environment data

Tab. 1 shows the results of the linear regression models for each city and all cities combined. In the regression models, the dependent variable is the average number of people per image in a hexagon; the independent variables are the number of cars, bicycles, buses per hexagon (as counted from the images), the number of amenities for the respective hexagon, such as restaurants, pubs, or cinemas (recreational); services such as banks, libraries, schools, etc. (data from OSM); the number of intersections; and the total meters of streets inside each hexagon.

As shown in Tab. 1, the number of people present in the urban space is highly correlated with the location of recreational amenities and places with more bikes. In addition, the relationship with motorcycles is similar to that of bicycles, which makes sense in the case of the Netherlands, where some motorcycles can use bike lanes. In addition, our results indicate that people tend to be in places with more intersections and denser in terms of street length. Even though a visual inspection of Figure 2 may suggest a negative relation between the presence of people and cars, no statistically significant relationship is found.

4 Conclusions and next steps

The use of images at the street level as input data can provide information to improve the understanding of the relationship between the urban space and the places where people have social interactions. Also, the results of data collection and image processing with a computer-vision-based method can be used to identify the areas most likely to produce social interactions in urban space. The potential of the proposed measurement and analysis method. The linear regression results indicate that for these three Dutch cities people tend to meet in places with a strong presence of recreational attractions and bicycles. Our study demonstrates how street-level images can

Table 1. Linear regression results for the three cities and all cities together. Columns Coef. and Test-t show the coeficients of each variable in the linear regression and test-t value, respectively.

	Delft		Gouda		Katwijk		All cities	
Indep. Vars.	**Coef.**	**Test-t**	**Coef.**	**Test-t**	**Coef.**	**Test-t**	**Coef.**	**Test-t**
bicycle	0.2550	13.662	0.589	17.704	0.7420	14.164	0.3519	22.642
car	-0.0005	-0.262	0.0035	1.500	0.0039	1.294	0.0022	1.598
motorcycle	0.6839	7.950	0.5738	4.609	0.7006	6.135	0.7911	13.111
bus	0.1968	1.829	0.4629	2.684	0.0874	0.368	0.2651	3.095
truck	0.1365	2.194	-0.0108	-0.155	-0.0136	-0.192	0.0591	1.496
bench	0.3888	3.430	-0.0317	-0.315	0.3299	1.748	0.2210	3.111
intersections	0.0250	8.192	0.0180	4.125	0.0154	2.932	0.0231	10.249
street length (m)	4.861e-05	3.142	8.587e-05	3.136	0.0001	3.123	6.094e-05	4.804
services	0.0975	2.970	0.0132	0.279	0.0602	0.505	0.0627	2.385
recreational	0.3873	22.429	0.4566	16.202	0.5561	2.070	0.3830	25.303

provide useful information to perform spatial analysis in cities. Object detection in urban images can be applied in different fields to understand patterns of urban design, residents' and visitors' behaviour, and municipal operations.

As part of ongoing work, we conduct a statistical analysis of the number of people per spatial unit across cities. Our next step is to advance our methods toward social interactions using F-Formations. Furthermore, we intend to enhance our regression techniques, e.g., by applying more advanced methods and ML techniques that account for spatial-autocorrelation and test different urban environment variables to identify the key determinants of the location of social interactions.

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