Automatic Mapping of Physical Urban Problems Using Remotely Sensed Imagery

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ABSTRACT

While big cities are expected to exercise cost-effective, evidence-based planning, many are under reactive management, facing simultaneous problems and limited resources. This project develops a proof-of-concept workflow for the automatic monitoring of physical urban problems by combining remote sensing for detection and cartography for visualization. The example problem treated was the obstructive parking of vehicles on pavements as proxy for restricted urban mobility. Nine aerial images of UK urban areas were processed by a deep learning object detector of standard cars, achieving an F-score of 70.72%. Two large scale map reports of 200m wide areas were produced, featuring car detections and overlaps with topographic mapping features. Complementary analysis included the calculation of total detection window overlap per roadside pavement and its change with time. The proposed method combines uniform city-wide coverage with fast interpretation and can inspire the development of professional urban planning tools.

KEYWORDS

Object Detection, Urban Monitoring

INTRODUCTION

The global trend of rapid urbanisation (Potsiou et al., 2010) entails planning challenges for modern cities. Large disorderly congregations of diverse and interdependent stakeholders create material problems regarding traffic, waste, infrastructure, air quality and health (Chourabi et al., 2012), amplified by outdated traffic-centered planning (European Commission and Directorate General for Mobility and Transport, 2017) and by individualist or traditionalist behaviours (Rode & Hoffman, 2015). Recognitions of the importance of urban space to quality of life have begun to appear at the international policy level (EEA, 2015), including the New Urban Agenda, a UN standard calling for robust science-policy interfaces, sharing mechanisms for globally standardised geographical information and transparent e-governance (United Nations Conference on Housing and Sustainable Urban Development, 2017). Sustainable Development Goal 11 of the UN 2030 Agenda pushes for ‘inclusive and sustainable urbanisation and capacity for participatory, integrated and sustainable human settlement planning and management in all countries’ (Rosa, 2017).

DOI: 10.4018/IJEPR.321156
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In line with the above, standardising the monitoring of urban environment quality bears promise in terms of evaluating the current state of infrastructure and planned interventions (Gould, 2011; Leach et al., 2019), but also in creating healthy inter-city competition (Giffinger et al., 2010). Many cities still obtain the state of infrastructure by chance observation of personnel working outdoors. Current monitoring suffers from small coverage, infrequency and unreliability, while legal demands are rising. 'Large amounts of costly technical evidence' are demanded by UK city councils towards local plan making decisions in periods of tight budgetary constraints (Harris, 2017).

The aim of this study was to develop a proof-of-concept for a digital tool that detects well defined manifestations of urban problems in remotely sensed imagery and produces cartographic visualizations to assist urban planners in efficient management, intervention prioritization, and policy.

To this end, an approachable instance of urban problem was found in pedestrian mobility obstructions. Specifically, the inconsiderate parking of vehicles in a way that obstructs pedestrian movement on street-side pavement – fully or partly occupying pedestrian space – was deemed suitable for testing an urban image detector due to the availability of detection software focusing on vehicles, as well as of appropriate geospatial representations of pavements in the UK.

Specific objectives were to:

1. Achieve workable accuracy in detecting cars in remotely sensed imagery.
2. Superimpose detections on topographic geospatial data, perform spatial analysis and output suitable large-scale maps.
3. Integrate the process into one application that conforms to determined user requirements.

The proposed solution involves the massive automatic interpretation of satellite and aerial imagery of urban environments using an appropriate Computer Vision (CV) object detector, with the goal of locating objects related to geographically definable urban problems and superimposing them on geospatial data to extract insight towards more effective urban planning. Existing approaches to gathering urban insight for planners were rejected because they are not scalable (field surveying and local urban sensors), not efficient (manual imagery interpretation, ground observation), not easily manageable and consistent (citizen reporting, big data), or too generic (esri™ geoprocessing tool). Additionally, a preliminary planner survey carried out before the analysis (see below) confirms the professional demand for a relevant tool, and justifies the current focus on automation.

The paper focuses on the demonstration of feasibility and potential in automatic detection, and not the development of a fully documented prototype application. The detection target is also not of primary importance. Parked vehicles serve as an example of freely definable problematic occurrences in the city. Furthermore, the paper only considers infrastructure and environmental issues.

BACKGROUND

In a global 2007 study (Potsiou et al., 2010), seven megacities suffered from largely mutual problems: high density, lack of green areas, loss of cultural heritage; unlawful development and city centre dilapidation; unsustainable land use; congestion and commuting problems; basic resource insecurity; and lacking basic services. In the early 2000s reference was made to pockets of deprivation, exclusion and run-down environments in even the most 'successful' cities (Carpenter, 2006) and an unsustainable quality of life, occasionally even in face of health risks (EEA, 2009).

Urban mobility, vital for keeping cities productive and for maintaining welfare, is threatened by traffic-centred planning (European Commission and Directorate General for Mobility and Transport, 2017) and by individualist or traditionalist behaviours (Rode & Hoffman, 2015). Pedestrians struggle with tight space, obstacles, pollution and risk of accidents in the majority of modern urban environments (Gehl, 2010). At the same time, however, a shift in focus is observed in EU mobility plan implementation guidelines: from traffic flow capacity to accessibility and quality of life, from infrastructure to cost- effective integrated actions; from expert exclusivity to interdisciplinary and participatory planning; from limited impact assessment to regular monitoring (Wefering et al., 2014).

Central among inhibitors of urban mobility is inconsiderate and obstructive parking, especially in regions with lenient traffic law enforcement (Bajçinovci & Bajçinovci, 2019). Its effects include increased accidents, severe access problems for residents and businesses, increased enforcement expenses, promotion of a disrespect for the law, increases in traffic congestion and deterioration of visual attractiveness (Cullinane & Polak, 1992). Traditional enforcement practices seem more irrelevant as cities grow larger without sustainable city planning (Bajçinovci & Bajçinovci, 2019). Figure 1 illustrates two examples of obstructive parking creating unfavourable conditions for pedestrians in a European city, what inspired this research into better monitoring.

In this context, innovative monitoring approaches have been moving away from manual data collection and onto urban sensing. New parking occupancy detection makes use of in-ground sensors, portable GPS-enabled cameras, video recording and license plate recognition (Dey et al., 2017), and even matching GPS trajectories of shared bikes to urban maps (He et al., 2018). The remote sensing of urban phenomena, utilising aerial or satellite platforms, is said to be entering a new era of ‘high-definition’ with studies in urban growth, morphology, biophysical characteristics and land cover (Weng et al., 2012), urban socio-economics (Patino & Duque, 2013; Stathopoulou et al., n.d.) and applications in urban problems (Carlson, 2003). Many private urban observation services have developed, including critical infrastructure assessment.

Satellite, aerial and Unmanned Aerial Vehicle (UAV) imagery is generally produced faster than is possible to manually process (Liu et al., 2017, Singh, 2019), making automatic interpretation necessary for wide geographical coverages. Numerous CV algorithms have been applied to optical overhead imagery, with machine learning detection and classification achieving human-like performance (Cheng & Han, 2016). Detectable urban objects include vehicles (Abraham & Sasikumar, 2014; Audebert et al., 2017; Eikvil et al., 2009; Leitloff et al., 2010; Razakarivony & Jurie, 2016; Tayara & Chong, 2018; Xueyun Chen et al., 2014), roads, buildings, solar panels and storage tanks (Mujtaba & Wani, n.d.; Tayara & Chong, 2018).

Modern urban planning applications include classifications of urban areas, impervious surface estimation, land use change tracking, services routing, green space mapping (*From Urban to Rural | GIM International*, 2020), and in the context of urban sprawl, detection of disused factories and unused parking lots (*Disused Factories and Satellites Helping Thwart Urban Sprawl | Research and Innovation*, 2016), understanding trends in street and car park usage (Kamenetsky & Sherrah, 2015). All of the above involve the use of remote sensing data in cartographic applications.

Attempts in integrating remote monitoring data into Geographical Information Systems (GIS) are accelerating, examples including a determination of parking lot occupancy (Yu, n.d.) and a classification of swimming pools in land parcels (Jha, n.d.). esri™, the market leader in GIS technology,

Figure 1.
Examples of obstructive parking in Ilisia, Athens (Lempesis, 2019)

is investing in deep learning applications, having recently launched a deep learning image classification geoprocessing tool and related projects (Singh, n.d.).

PLANNING SURVEY

A preliminary user survey was carried out during July and August 2019, aiming at obtaining a first image of existing user interests, concerns, and tool requirements, among 34 respondents from planning departments of the most populous Local Authorities and London Boroughs in Great Britain, some municipalities in Greece, and some academic professionals in related fields. There were 13 questions on respondent consent, identification and location, current city monitoring practices and potential future tool implementation. It is noted that six of the 23 respondents who made their location known were from Glasgow, UK. A summary of the survey findings follows.

The problems most visible to city councils under current monitoring are illegal parking, the condition of green spaces, unused land or abandoned places, urban sprawl and illegitimate development. Most councils monitor obstacles to pedestrian movement in some way, with the state of infrastructure and especially the road network being key priorities. Information collected includes problem location, description and classification. Information collection weighed towards ground observations by municipal employees (85%), including city technical services, with resident testimonials considered important. Dedicated surveyors are relied on in 20% of councils. Only 17% of councils monitor problems periodically by a set schedule (31% in the UK). The problems are usually registered in standard digital databases in about half of cases, with a 44% of respondents adopting geographical databases for storing city information.

A 40% of respondents confirmed that either coverage, frequency, accuracy or usefulness (comparability) of collected data, or combination thereof, is hard to achieve. Some answers hinted to the lack of technical capacity and expert skills, as well as the lack of a ‘strategic system for monitoring, funding and staffing in local agency under required needs,’ so that only the most urgent problems are ever studied. Irregular monitoring was said to lead to discontinuity, but the lack of staff, or the overwhelming workload of relevant officials persists.

Nine in ten respondents replied positively with respect to implementing a potential detection tool, with 62% considering implementation cost a significant factor. The most desirable feature (73%) was control over map output in terms of style, scale and content. More than half of the respondents would like the option to select the object types/categories detected, the detection algorithms and custom data input. Two interesting responses concerned integration: output maps should include existing and planned public apparatus, and results should be compatible with other internal GIS datasets.

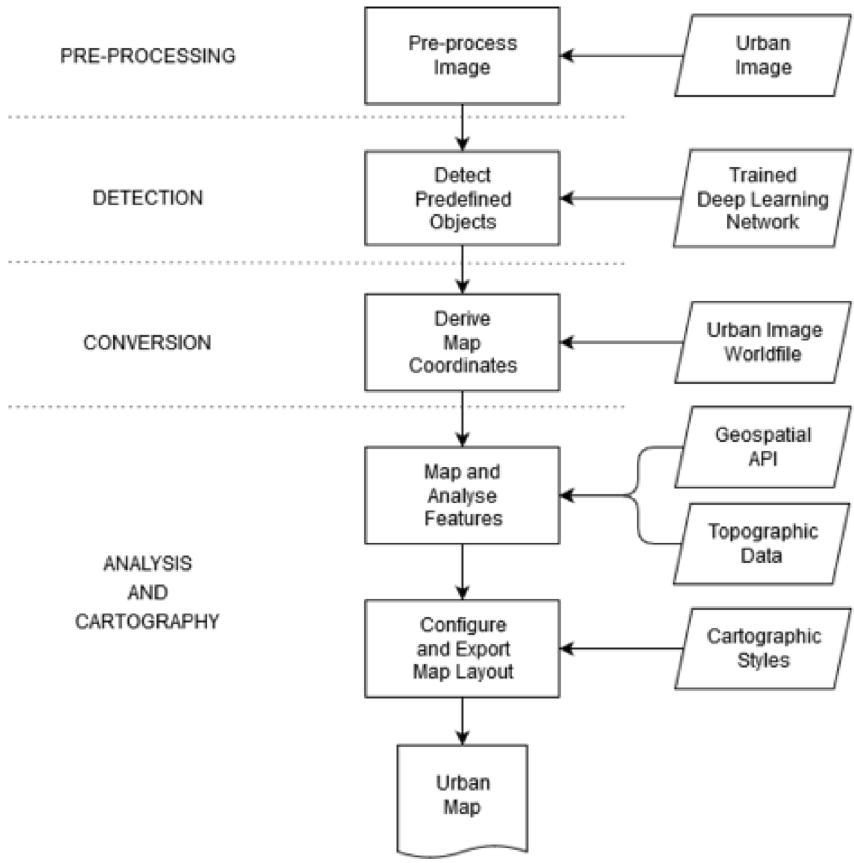
Some use cases were proposed by planning professionals: detecting long-term trends as well as shorter flows and relationships in the urban fabric; providing further evidence base for planning decisions and guidance; monitoring the condition of buildings; special parking restrictions; fault reporting in parallel with public reporting apps; detection of unlawful tree felling; loss of green space and unlawful development; and complementing site visits for a more complete picture. A concern was raised about the temporal responsiveness of remote imagery compared to sources like CCTV or citizen reporting apps.

Integration over a web map database would be beneficial to collaboration within organisations but also externally, linking with other planners, presenting results to the public or delivering open data. Simplicity and usability are called for to maximise user understanding and impact, meaning clear interface design, complete documentation, unambiguous cartography and strict definition of output data.

METHOD

Georeferenced overhead images were tested by a deep learning algorithm and output detections were superimposed on a detailed topographic backdrop in a GIS to generate spatial metrics (see Figure 2).

Figure 2.
General workflow



Data

The imagery consisted of nine aerial true-color captures by Getmapping Plc of various ground locations and dates between 2010 and 2015 (see Table 1). Sensor specifications can be found in (*Aerial Data - GB Imagery | Getmapping*, n.d.). The locations were chosen to represent a variety of urban landscapes, including motorway (A), suburbs (B), dense city centre (C, D, H, I) and industrial areas (E, F, G). Images B and E were used to test the main workflow and produce two urban map reports. Images H and I were used for complementary analysis.

The imagery was resampled into the detection network nominal input Ground Sampling Distance (GSD) of 0.15 m (see below), using cubic convolution. All areas of interest were clipped into 200 m squares. No images overlapped regions used in network training. Standard deviation (n = 2) contrast stretching with no gamma correction was applied. The resulting image reference system metadata and final pixel shape were validated through the respective image world files.

The Ordnance Survey (OS) MasterMap Topography layer served as topographic background for the UK regions. MasterMap is the most detailed set of topographic spatial data in Great Britain, with regular updates, consistent standards and detailed documentation (Survey, 2017). Furthermore, it is accessible to public services and city councils. Physical features are uniquely identified and linked to attribute themes. Of particular interest was the ‘Roads, Tracks and Paths’ theme, which includes Descriptive Groups ‘Paths’, ‘Railways’, ‘Road sections’, ‘Verges and Pavements’, further differentiated by other attributes.

Table 1.
Testing imagery from Getmapping Plc

			Easting (m)		Northing (m)	
ID	**Description**	**Capture**	**Min**	**Max**	**Min**	**Max**
A	Glasgow City Centre	02/09/2010	258010	258210	666040	666240
B	Paisley Suburb	08/05/2011	246760	246960	662470	662670
C	Birmingham City Centre	09/07/2013	406550	406750	287140	287340
D	Birmingham City Centre	09/07/2013	406435	406635	287010	287210
E	Birmingham Industrial	09/07/2013	407730	407930	286350	286550
F	Leeds Industrial Area	19/10/2000	431000	431200	434665	434865
G	Leeds Industrial Area	17/07/2017				
H	London Marylebone	04/05/2014	528800	529000	181450	181650
I	London Marylebone	07/06/2015				

Coordinates in British National Grid EPSG:27700
Ground Sampling Distance (Spatial Resolution): 0.25 m
Time of Capture Not Available.

Vehicle Detection

Object detection was carried out by a pre-trained deep learning network developed by the United States government Lawrence Livermore National Laboratory (LLNL) for governmental applications in traffic and parking volume monitoring, chosen due to its public availability and wide training sample base. The training dataset Cars Overhead With Context (COWC) contained aerial samples (standardised GSD 0.15 m from unspecified original resolutions), at six developed cities around the world, of 32,716 unique annotated cars (as well as vans and pickup trucks but no larger vehicles) with marginal context and 58,247 unique negative examples. The network ResCeption architecture achieved precision and recall rates of 92.59% and 96.15% in development tests, respectively (Mundhenk et al., 2016).

Testing was carried out using the Caffe Deep Learning Framework (Jia et al., 2014) in CPU mode. Imagery was scanned by a window of 224 by 224 pixels (including a 32 pixel margin) with a horizontal and vertical stride of 8 pixels. Each window was forwarded to the network and yielded a probability of car-containment. Windows over the 0.75 threshold were non-maximum suppressed with a maximum overlap of 20 pixels. Detections were plotted as 48 by 48 pixel rectangles (equivalent to 7.2 m, the maximum vehicle size permitted by LLNL) around their central pixel. The list of detection pixel coordinates was converted into metres from origin (Easting-Northing pairs) by multiplying by pixel size. North-South pixel orientation and projected length units were assumed.

The detection accuracy was assessed manually over the nine aerial images (A–I) following (Mundhenk et al., 2016). Detections were labelled as true positive (TP), if they contained more than half a car and false positive (FP) if they contained less than half a car or if another true positive pointed to just the same car. Undetected cars and detections covering more than one car yielded false negative (FN) for every extra car. Rates of Precision P (fraction of detections made that were true) and Recall R (fraction of existing objects that were detected) as well as the F-score (a joint measure of P and R) were calculated according to Equations 1 to 3 for $\lambda = 0.5$ (area overlap between correct detection and object) and $\beta = 1$ (weight coefficient for relative importance of P over R) as per (Cheng & Han, 2016).

$$P = \frac{TP}{TP + FP} \tag{1}$$

$$R = \frac{TP}{TP + FN} \tag{2}$$

$$F = \frac{PR}{P + R} \tag{3}$$

Geospatial Integration

The geospatial library PyQGIS was used to integrate the detection coordinate list with underlying topography (see Figure 7 in Appendix 1). The topography layers were clipped to the rectangular bounding extent of the detections layer, to improve geoprocessing performance. A 100 m buffer of the actual extent was used to avoid predicate problems in spatial joins. Detection points were attributed the fields of their underlying Topographic Area and cars per Topographic Area type were counted.

The available detection algorithm did not allow for the exact localization of overhead car footprints but only square windows (small image crops) of high probability of car-containment. Consequently, cars that were parked next to pavements had windows that partly covered roadside areas, and cars parked on the roadside had windows that partly covered roads. To get around this, the ratio of road area covered by each window was calculated as per Figure 8, Appendix 1, to indicate a probability that cars were on the road.

Layer symbology was configured by precompiled QGIS style files. This provided modularity in cartography as styles were decoupled from the source. An A4 layout at scale 1:1,250 was chosen to combine the large scale necessary for local urban map reports or field surveys with a feasible image size for timely processing using available resources. A list of the number of detections per topographic area within the map extent was output below the annotations. The map extent was automatically configured using the input imagery, and the layout was exported in PDF format.

To demonstrate the quantitative capability of the method, an additional workflow obtained a measure of 'vehicle pressure' on individual geospatial pavement features. This 'vehicle pressure' could be directly used by planners to sort features and prioritize intervention across the city. The multiple detection window polygons were merged, intersected with the topographic area layer and dissolved by the unique OS Topographic Identifier (TOID, across all OS mapped features), to get an aggregate polygon per pavement feature. The area of each of these polygons was calculated into a new attribute, which was then joined to the topographic layer using TOID. Pavements were symbolised according to the 'Detection Overlap Ratio', i.e. the ratio of window area to total pavement area (see Figures 5 and 6).

The above process was repeated for two images of identical location to demonstrate the potential for temporal comparison and resulting detection window areas were joined to one aggregation topography layer. This layer was symbolised by the difference in Detection Overlap Ratio between image capture dates, reflecting the temporal trend. Finally, heatmap-style symbology was tested for potential visualization implementations in city-wide maps, where car detection density was shown as a proportionally red overlay.

RESULTS

The variation of detection performance across the images was considerable, inviting further testing, but some results were adequate for the proof of concept. Workable results were obtained for aerial imagery (see Table 2). A large discrepancy was observed in Recall between older (A, B, F) and more recent imagery. The photographic clarity of the lowest ranking image F was visibly inferior, potentially attributable to changes in photographic equipment. In post-2011 imagery, the algorithm precision was uniform across different urban landscapes. The small number of false positives was spread throughout the images in high-contrast edges of buildings and rooftops, and dense details in yards or shaded areas.

Table 2.
Detection accuracy across nine aerial images. F-score shows high variation in performance

ID	Year	Count	Detections	Precision	Recall	F-Score
					%	
E	2013	167	170	94.12	95.81	94.96
H	2014	179	157	99.36	87.15	92.86
D	2013	127	127	90.55	90.55	90.55
C	2013	230	192	98.44	82.17	89.57
G	2017	275	222	96.85	78.18	86.52
I	2015	89	58	98.28	64.04	77.55
B	2011	69	38	100.00	55.07	71.03
A	2010	110	21	90.48	17.27	29.01
F	2000	88	3	66.67	2.27	4.40
Average				92.75	63.61	70.72
Standard Deviation				10.42	33.27	32.14

Two urban map reports were produced (Figures 3 and 4). The former portrays a suburb of Paisley, Glasgow and the latter a local industrial street in Birmingham. The layouts were intended to support sketching, ideating, communicating and monitoring solutions, as well as engaging the public. The maps demonstrate the potential for visualising pattern distributions, e.g. a high parking demand in the industrial area combining with a lack of available space leading to pavement parking. The automatic geospatial metrics (see below) take a quantitative perspective and could help standardize this pattern recognition.

Images H and I were chosen to demonstrate quantitative results visualization and temporal comparison. An extended map illustrating ‘vehicle pressure’ would provide a straightforward means of intervention prioritisation (Figure 5). The comparison of imagery at a constant location, combined with uniquely identifiable topographic features means problems can be tracked through time (Figure 6), and location history becomes accessible in a city-wide database scheme. Fast deteriorations of public space quality or other trends can be directly queried in the database or GIS.

It is worth noting the flexibility in defining observable metrics. Some other possibilities include the proximity of car detections, the number of problematic cases per neighbourhood classification, or the relationship of overlaps to the width of sidewalks. The exact definition of what is problematic (here a detection overlapping pavement over 50%) is also an independent variable, meaning the planner can handle edge cases (see Figure 3) according to their implementation.

DISCUSSION

Limitations

The main limitations of the process lie with imagery capture and base map data availability.

The nature of remote imagery presents some difficulties in urban sensing. The photographic angle may make some buildings partially hide adjacent ground, and vegetation may often block portions of vehicles. This might become an issue in detecting smaller objects such as hydrants or potholes, among dense construction. Numerous cloud removal techniques exist but may depend on ancillary data (Eckardt et al., 2013). Simply picking imagery from different providers is a viable option. Another noteworthy limitation is the lack of exact timestamps of image captures by the chosen provider which

Figure 3.
Urban map export for Image B, featuring a quiet residential area. The response to edge cases is observed, i.e., vehicles fully on private property and vehicles right on the edge of the sidewalk

Figure 4.
Urban map export for Image E, featuring a busy industrial area. Some sidewalks are clearly more obstructed than others

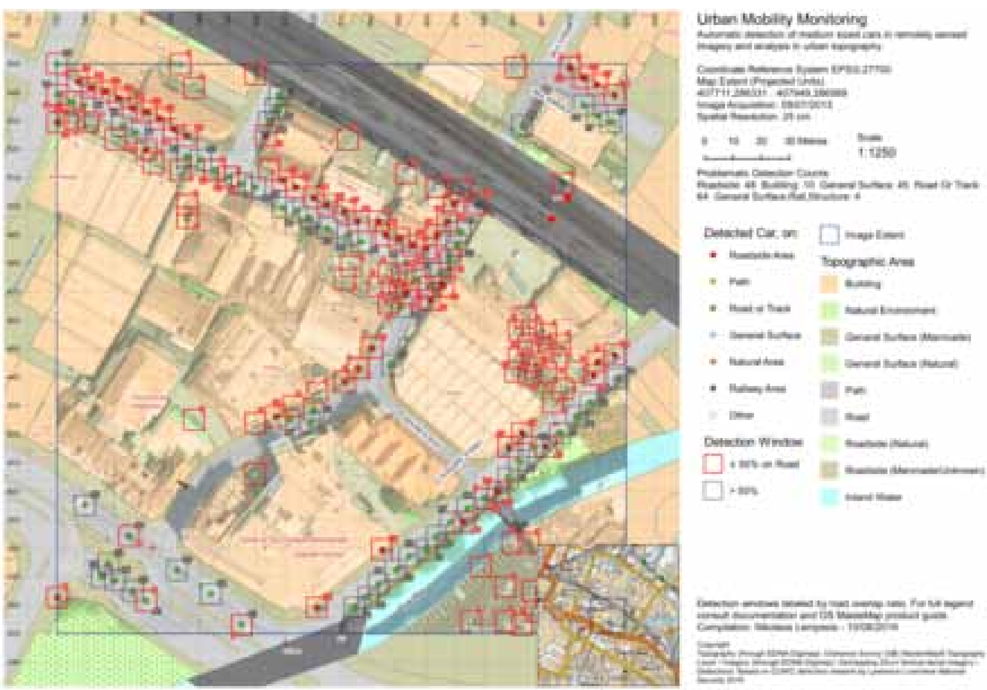


Figure 5.
Vehicle pressure on pavements (from Images H and I). Detection window overlap ratio. Topographic data from: Getmapping (2000–2017) and OrdnanceSurvey(GB) (2019)

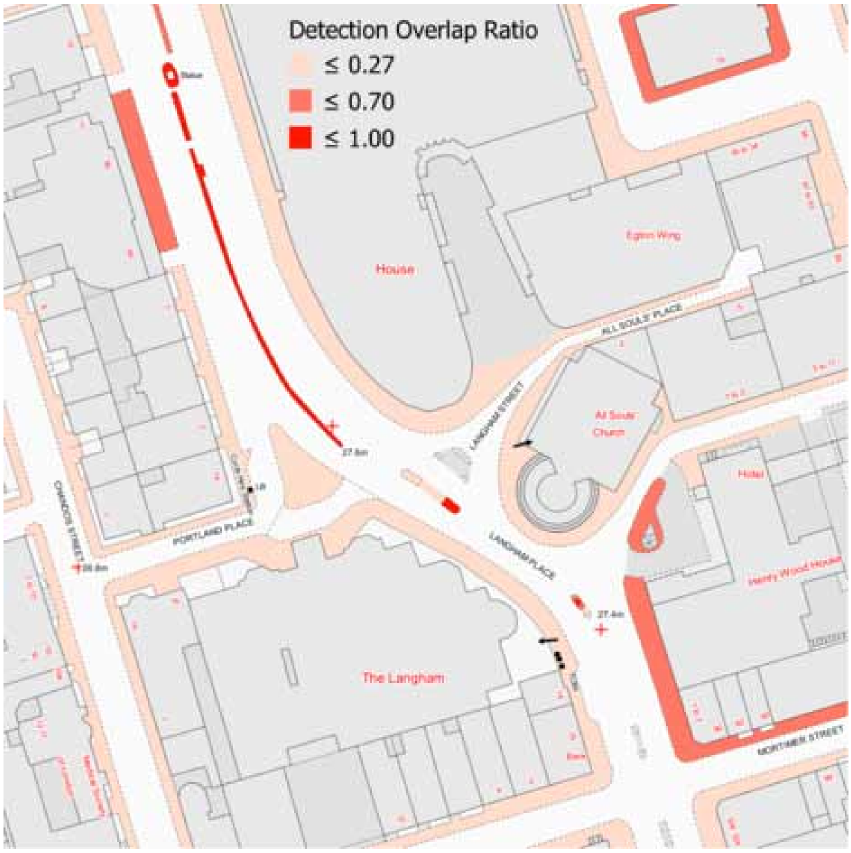
limits the temporal precision of scene comparisons. Any ensuing statistical analysis will be dependent on available information within remote sensing and mapping data.

OS MasterMap features accuracy, completeness and continuous support, and offers a range of opportunities for analysis. Outside countries with strong geospatial infrastructure and accurate topographic mapping, especially where urban problems are most prominent, however, such data is not available. A very interesting alternative would be OpenStreetMap (OSM), a free, global, crowd-sourced map database with a versatile attribute scheme and large potential for innovation in planning applications. At the time of writing, roadside pavements are only recorded as attribute entries for linear road features, making pedestrian mobility evaluation difficult. There is considerable active research on OSM data quality (Lin, 2011), and exploitation in the present application should be further examined.

Evaluation

Generally desirable imagery characteristics were identified: wide coverage; high spatial resolution; low inclination (capture zone near nadir); capture times with short shadows; and accessibility. However, the specific requirements leading to optimal detection accuracy will ultimately depend on the characteristics of the detection algorithm. The accuracy of the ResCeption algorithm was inhibited by using imagery out of specification, but in professional applications detectors will be trained on target imagery. Object detection usually makes use of true-colour composites, but the potential of using

Figure 6.
Vehicle pressure on pavements (from Images H and I). Ratio change in 2014–2015. Topographic data from Getmapping (2000–2017) and OrdnanceSurvey(GB) (2019)



multispectral data in this application field could be examined, as it could enable the discrimination of otherwise unseen urban details, e.g. moving objects, vegetation health or ground pollution.

The contributing data layers involved varying geolocation accuracies (see Table 3). The geospatial analysis of detections would be meaningless if the horizontal accuracy of any utilised data (topography, imagery or other) was comparable to the size of detected objects.

Table 3.
Horizontal accuracy of mapped layers

Layer	Horizontal Accuracy Indication
OS MasterMap	Absolute 0.8 m at 95% Confidence
	RMSE 0.5 m
Getmapping Aerial	RMSE 1.0 m
WorldView-2 Satellite (for reference)	3.5 m CE90 Without Ground Control

RMSE: Root mean square error between observations.
CE90: Circular error at the 90th percentile.
Sources: (OS MasterMap Topography Layer Support 2019; DigitalGlobe 2013; Vertical Aerial Photography and Digital Imagery 2010)

Aerial imagery is expected to be adequate, but satellite accuracy is similar to the short dimension of standard cars and analysis of smaller objects may be limited. The horizontal accuracy of satellite imagery depends on numerous factors and changes with time. The geolocation accuracy of orthorectified imagery will generally be lower due to the additional correction using a digital elevation model (DigitalGlobe, n.d.). Additionally, the detection algorithm plays a significant role in how precisely it can pinpoint detections with respect to the image. The transformation of data into different coordinate systems may also lead to multi-metre error. With respect to cartography, features should be accurate within 0.5 mm at map scale, which is 0.6 m at 1:1250 (Longley, 2015).

The concept underlying the method involves a mass-treatment of the urban environment, in that it analyses urban areas in a uniform manner not accounting for vernacular customs, popular preferences, history or identity. The solutions inspired by the generated insight do not have to be equally mass-solutions, or treat city regions uniformly, and locally tailored approaches are possible. Attention is drawn to Section 8 of the Royal Town Planning Institute Ethics and Professional Standards Guide which stresses the need for professional inclusive consultation of affected communities in proportion to the degree of planning intervention (Royal Town Planning Institute, 2017). Calls have been made for fundamental changes in urban life styles and needs, and concerns are raised on the effectiveness of the technocratic focus of smart city workflows (EEA, 2009). Following suggestions by (Liu et al., 2017), this urban evaluation method relates to a tool, not a directive, and should be treated by professionals as indicative.

Furthermore, the systematic collection of location based involuntary overhead data is sensitive in terms of ownership, privacy and security. Urban sensing must be subject to public acceptance and privacy laws (Potsiou et al., 2010). Software implementation would require rigorous contract management, user training and interoperability with other IT systems used by city councils (Harris, 2017). How automatic detection might adapt to address these issues is a stimulating area for further research.

Opportunities

Planners were found to avoid satellite sources due to limited investigation in urban applications, lack of expertise in imagery handling, and low resolution (Carlson, 2003), but they are crucial as they unlock the potential for wide coverage, standardised and cost-effective analysis. The satellite acquisition properties are constant and this may benefit international standardisation efforts, especially as spatial resolution and cost-effectiveness are rapidly improving. The public sector would ideally benefit from free imagery and in many cases national geospatial infrastructures may provide an answer ("Space for Smarter Government Programme (SSGP)", n.d.; "Public Sector Bodies Can Access Aerial Photo and Height Data for Free — Getmapping", n.d.; "7 Top Free Satellite Imagery Sources in 2019", n.d.). As an alternative to the training of a completely new detection network to handle satellite imagery, retraining an existing network using the Transfer Learning technique can save resources without significantly compromising accuracy (Donahue et al., 2013; "How to Retrain an Image Classifier for New Categories — TensorFlow Hub", n.d.). An example of a transfer of an aerial detector to the satellite domain can be found in (Cao et al., 2016). Under professional implementations, strong computer equipment would process a square area the size of central London, about two miles wide (McDonald & Swinney, 2019), in under one hour ("Running Caffe AlexNet/GoogleNet On Some CPUs Compared To NVIDIA CUDA - Phoronix", n.d.). The performance limitation is further minimised by the late emergence of cloud services offering state-of-the-art, fast machine learning computation at affordable prices.

To extend the potential of geospatial integration, Image Semantic Segmentation may be utilised, a deep learning technique classifying image content at the pixel level. Vehicle detections could be converted to geospatial polygons corresponding to the overhead pixel footprints, making exact overlap and orientation analysis available.

Concerning the detection target, suggestions for detection object types in future implementations include signage, railings, waste bins, litter, road markings, potholes, pavement cracks, pavement surface and pedestrians. State of infrastructure analysis could expand to unused parking space, vegetation health, illegitimate development and urban sprawl. Expanded target sets would require dedicated detector networks. The geospatial processing can be developed in many directions. Vehicular density may indicate parking demand and may be linked to proximity to services or safety risks. City-wide parking occupancy may become measurable if parking places are mapped. In terms of pavement obstacles, the most affected areas may take priority in ground survey and intervention. Detectable objects like misplaced garbage, signage and outside seating may be considered in combination in terms of spatial arrangement for analysing complex mobility problems.

The above suggestions are particularly relevant when considering the potential for UAV (drone) surveys in cities. Given the reduced flight height, UAVs exhibit unparalleled resolution for the cost and easiness of capture. The sacrificed areal coverage may not be detrimental to urban applications.

Quantification of mobility through walkability indexes can also be considered in detection (Amoroso et al., 2012; COEH, 2011; Sousa et al., 2019; Tribby et al., 2016). Temporal analysis may reveal repeatedly and disproportionately burdened areas. Temporal trends can be used to monitor long-term pressures or the performance of past interventions and obtain the quantification necessary for evidence-based planning.

The map output may adapt to address different problems, including small scale maps showing frequency distributions and emphasising patterns in whole cities or quarters, or large scale maps overlaying urban problems on other thematic data, such as water infrastructure. In all cases, the maps presented here were strictly for demonstration of method potential.

In practical terms, urban planners who would want to enhance monitoring, would have to clearly define the geospatial manifestation of the analyzed problem, define the required detection targets, desired output visualization and action plan, obtain a relevant object detector and follow the above methodology. The steps above are notably open to participatory practices (problem definition), as well as the outsourcing of technological (and not directly planning-related) work to industry.

CONCLUSION

The aim of this project was to develop a proof of concept for a digital tool that detects urban problems in remotely sensed imagery and produces maps to assist urban planners in management and policy. The focus was on obstructive vehicle parking occupying pavement space and hindering pedestrian mobility.

A preliminary user survey was carried out to gauge the interest of professionals for a potential urban detection tool. The most important findings were that: monitoring currently mostly comes in the form of observations by municipal employees; irregularity in data capture affects planning priorities and often means that only urgent problems are dealt with; there is willingness to improve the monitoring process and the opportunities of digitisation and automation are understood.

Objective 1 was carried out successfully by automatically interpreting aerial urban imagery using an open-source CV object detector to detect standard sized car locations with workable accuracy (F-score 70.72%). Objective 2 was achieved by integrating detection results into existing backdrop topographic data. A workflow was developed for the semi-automatic production of single page 1:1250 map reports of detections and analysis results. Two example map exports were provided for Paisley and Birmingham, UK. Some complementary geospatial analysis, involving feature-based detection counts and temporal comparison between consecutive years showcased the potential for additional planning insight. Partial progress was made towards Objective 3. This was mainly due to the diversity of user requirements discovered in the relevant survey. Fully executing identified user requirements into an integrated application will require a production application development process.

The overall method was justified in terms of ease and cost of implementation, and the workflow is replicable with free software (Caffe, QGIS) and a personal computer.

This project has shown that the combination of automatic object detection in remotely sensed imagery with existing geospatial data can deliver efficient monitoring of well defined manifestations of urban problems and cartographic visualizations to assist urban planners in efficient management, intervention prioritization, and policy. A proof of concept for a smart city tool capable of long-term impact was developed. New ways to monitor the complexities of the urban environment will aid to combat unsustainable living.

ACKNOWLEDGMENT

Thanks to Dr. Brian Barrett (University of Glasgow) for supervising and PhD candidate Anastasios Stamoulakatos (University of Strathclyde) for the support.

CONFLICT OF INTEREST

The author of this publication declares there is no conflict of interest.

FUNDING AGENCY

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. The research was supported by the University of Glasgow.

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APPENDIX 1

Figures 7 and 8 illustrate the geospatial manipulation of detection and topography data to reach results.

Figure 7.
Geospatial integration workflow

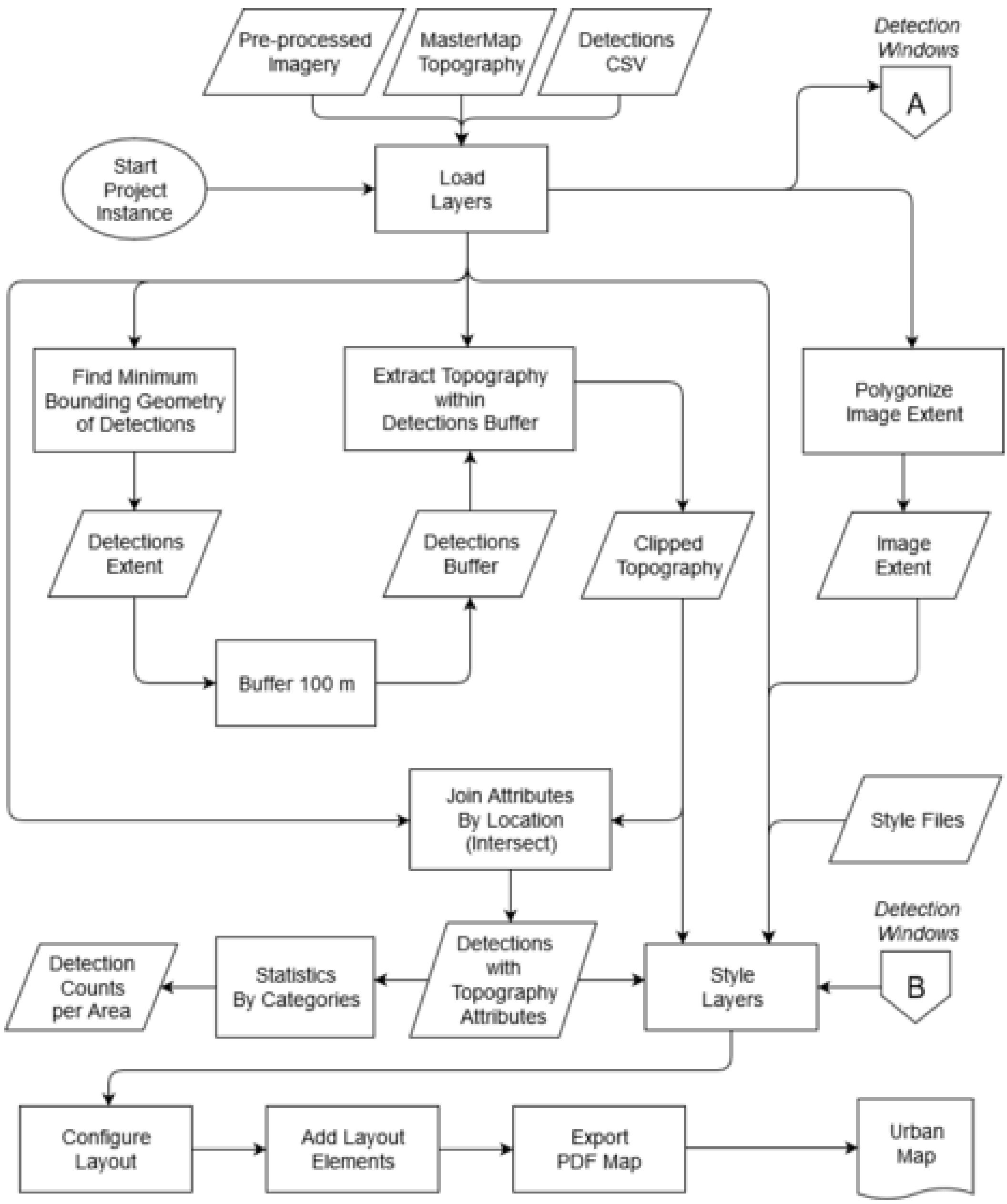
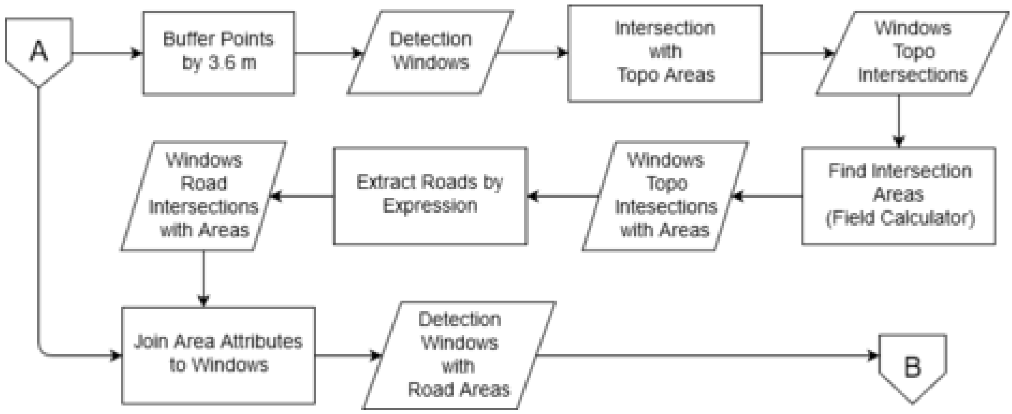


Figure 8.
Calculation of detection windows road areas



APPENDIX 2

This appendix provides the questions of a questionnaire survey distributed via e-mail to professionals engaged with the field of urban planning, in local governance, academia or out of personal interest, from early July to the middle of August 2019. Full consent was established before respondent participation and anonymity was respected where requested. Participant contact information and city of residence/work was requested. None of the questions (except for consent and position/role) were mandatory. The questionnaire was hosted by Google Forms.
Positions/roles of respondents included:

- Planning Officer
- Senior Planner
- Postdoctoral Researcher
- Concerned Urban Resident
- Planner (Development Management)
- Town Planner
- Planner
- Associate Professor
- Built Heritage Officer
- Urban Planner
- Technical Officer
- Freelancer
- GIS Officer
- Commissioner for Urban Development

Question 1: What problems does your city monitor in the physical urban environment?
Question 2: What kind of information is collected?
Question 3: How is this information collected?
Question 4: How often?
Question 5: How is the information stored?
Question 6: What challenges do you face in monitoring urban problems?
Question 7: Would you implement an automated remote monitoring solution where feasible?
Question 8: What tool features would be necessary?
Question 9: Why would you benefit and what would you use the tool mostly for? Would you like to share additional thoughts, or feedback?

Nikolaos Lempesis is a practicing cartographer and geospatial developer with a background in Civil Engineering. He works on web map application development and takes interest in the impact of cartography on urban planning and digitization. He holds an MEng Civil Engineering from the University of Bristol, UK, and an MSc Geoinformation Technology & Cartography from the University of Glasgow, UK.