Chapter 16
Unsupervised Deep Learning to Explore Streetscape Factors Associated with Urban Cyclist Safety

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Abstract Cycling is associated with health, environmental and societal benefits. Urban infrastructure design catering to cyclists' safety can potentially reduce cyclist crashes and therefore, injury and/or mortality. This research uses publicly available big data such as maps and satellite images to capture information of the environment of cyclist crashes. Deep learning methods, such as generative adversarial networks (GANs), learn from these datasets and explore factors associated with cyclist crashes. This assumes existing environmental patterns for roads at locations with and without cyclist crashes, and suggests a deep learning method is able to learn the hidden features from map and satellite images and model the road environments using GANs. Experiments validated the method by identifying factors associated with cyclist crashes that show agreement with existing literature. Additionally, it

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revealed the potential of this method to identify implicit factors that have not been previously identified in the existing literature. These results provide visual indications about what streetscapes are safer for cyclist and suggestions on how city streetscapes should be planned or reconstructed to improve it.

16.1 Introduction

Cycling as an active and sustainable transportation mode is associated with health, environmental and societal benefits. Increased uptake of cycling reduces congestion and pollution, decreases energy consumption and supports healthy and sustainable lifestyles [1]. Increasing the use of bicycles is being supported as a transport policy in many countries [2]. However, cyclists are vulnerable road users and are over-represented in crash statistics [3]. The crash risk associated with cycling discourages people from adopting cycling as a main transportation mode [4] and improving both perceived and actual cycling safety, is key to promoting cycling [5].

Considerable research related to cycling safety focuses on intersections [6], roundabouts [7], and cycle tracks [8] using traditional methods applying either in-person surveys or video footage observation and analysis; all very time consuming and expensive approaches [9]. Until now machine learning, in particular, the use of deep neural networks, has seldom been applied to the study of cyclist crashes.

While particular reasons may apply to a specific cyclist crash, the aggregation of crashes across time and multiple locations infers an array of relations between the road environment and cyclist crashes. We hypothesise that there exist different high-level hidden features in road environments of crash domain and non-crash domain that are difficult to identify by examining individual crash locations. To identify these hidden patterns, we use GANs, a class of algorithms for unsupervised machine learning, that are able to model the distribution of unstructured datasets with the potential to extract high-level features. GANs were first developed by [10] to reconstruct images, and have been widely applied to convert low-resolution images into high-resolution images [11], inpainting [12] and style transfer [13]. In particular, Wijnands et al. [14] suggested GANs as a method for computer-generated design interventions to improve citizens' health and well-being.

Publicly available big data such as street view images, maps and satellite images capture road environments from different perspectives and provide information of different abstraction. Street view images offer street-level imagery and give detailed information about objects in the streetscape. On the other hand, maps are more abstract and semantically rich, and provide not only locations and boundaries of visible objects such as roads, parks, buildings, rivers and facilities, but can also provide additional information such as public transport routes and terrain. Finally, satellite images capture widespread heterogeneous information that is usually not captured by maps, such as lane markings, road surface types, the density of trees and the shadow of buildings. In this paper, we use GANs to encode the road environments contained in map images, and to extract the hidden features for urban road environments of crash and non-crash domains. The results provide unique insights between road environments of crash and non-crash domains.

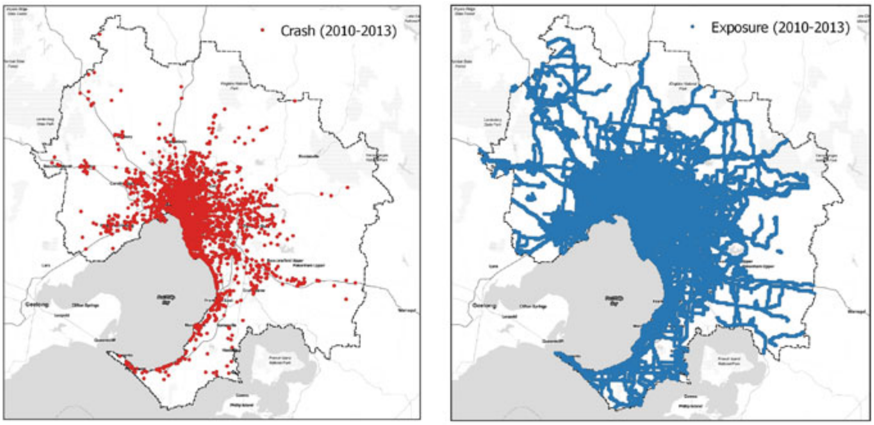
16.2 Methodology

16.2.1 Data Source

The study region is the Greater Melbourne metropolitan area (Australia), which has a population of almost five million. Of special note to this study, Melbourne has the largest urban tram network in the world [15].

This paper uses publicly available datasets for cyclist crashes recorded by the state road authority—VicRoads. In total, 5,156 crashes were recorded from January 2010 to December 2013 in Greater Melbourne (Fig. 16.1a). For exposure data, we used the anonymized bicycle trips recorded by volunteer users of the RiderLog smartphone application from 2010 to 2013 [16].

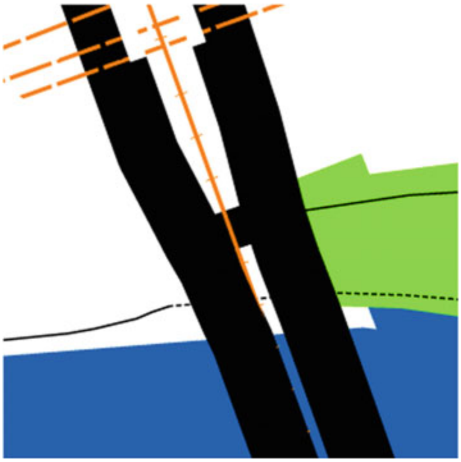
Google Maps and satellite images, were downloaded at sampled locations at a resolution of 320 × 320 using the Google Maps Static API. We used a zoom level of 19 and turned off the visibility of all labels. For Google Maps images, we eliminated most geographic characteristics and showed only parks, roads, transit lines, transit stations and bodies of water. We defined a colour scheme for Google Maps images



(a) Bicycle crashes. (b) Bicycle exposure.

Fig. 16.1 Cyclist crashes and bicycle exposure in Greater Melbourne

Fig. 16.2 Example of a Google Maps image



of white for image background, black for roads, blue for water bodies, orange for transit lines and green for parks (e.g. see Fig. 16.2).

16.2.2 GANs

GANs are neural network architectures, which simultaneously train a generative network called generator and a discriminative network called discriminator. The generator is a decoder function, but instead of reconstructing the inputs, it can work on any representation in the latent space. The discriminator takes both the generated images and images from the training dataset as inputs, and returns probabilities indicating how likely the input images are true images.

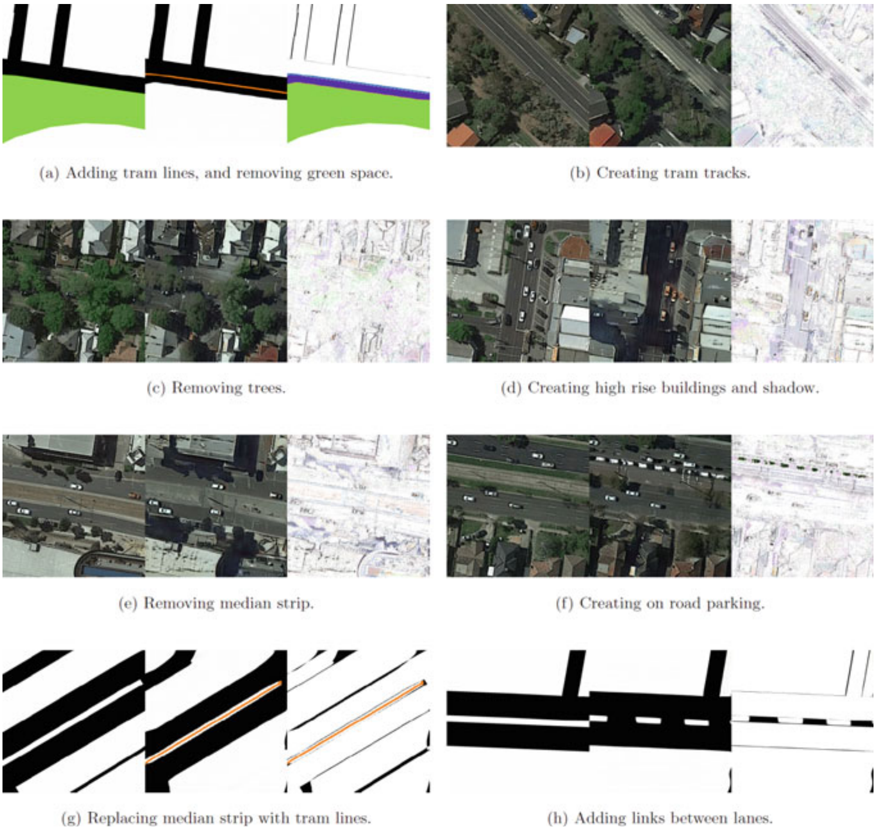
The generator's training objective is to generate images that cannot be identified as fake by the discriminator, while the discriminator tries to improve its capacity of detecting the fake images. During training, the generator learns to model the data distribution of images from the training dataset, and the discriminator learns to model the boundary of data distributions between images from the training dataset and images produced by the generator.

For a well-trained GAN, if the input is an image from one domain, then the generator can be used not only to reconstruct the input images back to its own domain, but also to generate images into a different domain (i.e. image translation). To observe the differences between crash domain and non-crash domain, we can translate images from one domain to the other and compare the changes of those images before and after translations. This paper used the GAN implementation developed by Liu et al. [17].

16.3 Experiment

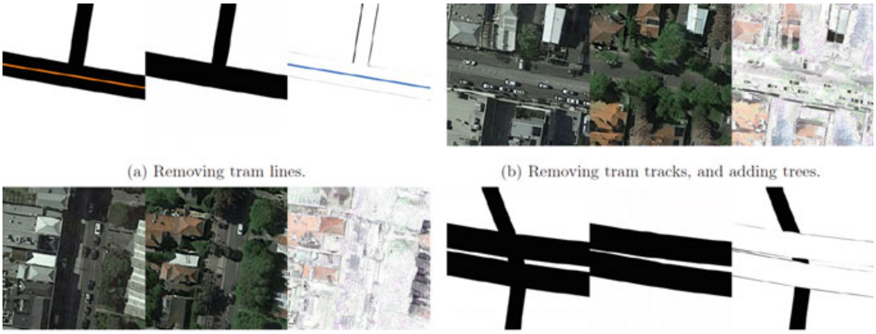
In this experiment, we sampled training datasets from only on-road bicycle networks. In total, 1,712 locations were sampled for crash domain, and 2,061 locations were sampled for non-crash domain.

Translation from non-crash domain to crash domain identified a few factors: Tram lines are associated with more cyclist crashes (Fig. 16.3a, b); green spaces are associated with a decrease in cyclist crashes (Fig. 16.3a, c); and road environments with high-rise buildings on roadsides casting big shadows are associated with increased crashes (Fig. 16.3d created a high-rise building using concrete ground for car parking). Figure 16.3e removed the median strip that separates traffic from opposing lanes on divided roadways and placed pavements at the same position. Similarly, in



(a) Adding tram lines, and removing green space.
(b) Creating tram tracks.
(c) Removing trees.
(d) Creating high rise buildings and shadow.
(e) Removing median strip.
(f) Creating on road parking.
(g) Replacing median strip with tram lines.
(h) Adding links between lanes.

Fig. 16.3 Themes observed when translating images from non-crash to crash domain. Each subfigure shows three images: the input image (left), the generated image (middle) and (right) the differences between the input image and the generated image



(a) Removing tram lines.

(b) Removing tram tracks, and adding trees.

(c) Removing on road parkings.

(d) Replacing intersections with mid-blocks.

Fig. 16.4 As Fig. 16.3, but from crash domain to non-crash domain

Fig. 16.3f, the median strips that separate tram tracks from roadways on both sides were removed, and the median strip on one side was replaced by on-road parking.

Another key observation is that the tram tracks in Fig. 16.3f have also been removed and replaced by roadways. Note that, the tram tracks in Fig. 16.3b are different from the tram tracks in Fig. 16.3f. The tram tracks in Fig. 16.3f have median strips on both sides, while the tram tracks in Fig. 16.3b do not have median strips. The tram tracks in Fig. 16.3b share road space with vehicles, i.e. vehicles can directly run on tram tracks. Comparing the translation in Fig. 16.3b which created tram tracks on existing roadways and the translation in Fig. 16.3f which removed tram tracks, we identify that tram tracks which share road space with vehicles are associated with increased cyclist crashes, while tram tracks separated by median strips are associated with decreased cyclist crashes. Figure 16.3g in which median strips were replaced by tram lines and Fig. 16.3h in which links were created between lanes on divided roadways both confirm that separated traffic is associated with decreased cyclist crashes.

The reverse translation from crash domain to non-crash domain confirms that the removal of tram tracks which share road space with vehicles are associated with decreased cyclist crashes (Fig. 16.4a, b). From Fig. 16.4b, we can observe that the tram tracks share space with vehicles, and two vehicles are running on the tram tracks when the satellite image was captured. Figure 16.4c shows the removal of road parking, which is consistent with the reverse translation in Fig. 16.3f. Figure 16.4c also shows the replacement of high-rise buildings with low buildings in the translation and the shadow with trees on-road sides, which is consistent with the reverse translation in Fig. 16.3d. Figure 16.4b and c both show an increase of green space. Besides the above themes which are consistent with the reverse translation, intersections have been replaced by mid-blocks in some translations (Fig. 16.4d).

Figure 16.4b and c also show a change of roof colour of buildings from silver to brick red. In Melbourne, most of the buildings in business or industry areas are high-rise buildings with silver colour top, while most of the residential areas have lower buildings with brick red colour. Residential areas generally have low traffic than business areas. Traffic factors have not been considered in this experiment, but the availability of high-quality exposure data and traffic volumes data will allow the method to explore those factors in more specific areas such as highly used intersections in CBD areas, and produce more detailed results.

16.4 Discussions

16.4.1 Summary

This experiment sampled training datasets from on-road bicycle networks. For on-road bicycle networks:

- Tram tracks are generally associated with more cyclist crashes, except for tram tracks that are separated from other traffic.
- Road environments for non-crash locations tend to have more green space (trees or grass), may indicative of density.
- Road environments with high-rise buildings casting shadows on roadsides are mostly seen in the crash domain.
- Intersections are associated with more cyclist crashes.
- On-road parking is associated with more cyclist crashes.
- Median strips are associated with reduced cyclist crashes.

Generally, these identified factors have been suggested previously in other studies, providing confidence in the presented methodology. Vandenbulcke et al. [9] found that a high risk is statistically associated with the presence of on-road tram tracks, complex intersections, and proximity to shopping centres or garages. Several other studies have also confirmed that tram tracks are strongly associated with bicycle crashes [15]. For example, Teschke et al. [18] found that for cities with extensive use of trams (or streetcars), one-third of cyclist crashes had directly involved tram or train tracks. Melbourne has the largest mixed traffic tram network in the world. It has also been found that on-street parking is associated with increased crash risk for on-road cycling [2], and separating bicycles and motor vehicles prevent the two modes from colliding [3].

16.4.2 Interpretation

The method is not intended to provide direct solutions to the problem of cyclist crashes, and does not diagnose the cause of cyclist crashes, which can be very diverse and are specified on the accident report from police, but investigates underlying factors. This method is an analytic tool that takes advantage of the increasing availability of big datasets, computing power and the advances of deep learning techniques, to analyse the road environments or even neighbourhood of locations that have cyclist crashes from a new perspective.

Generally, this method helps to achieve the fundamental target of still reducing cyclist crashes while promoting more cycling by serving three purposes:

- The method helps gain a better understanding of what factors are associated with cyclist crashes.
- The method can provide suggestions on what road environments are more likely to have less cyclist crashes than others, therefore redirecting cyclists to take certain routes.
- The method can provide suggestions on how to design city streets to reduce cyclist crashes.

16.4.3 Limitations

This paper investigates the factors associated with bicycle crashes based on imagery training, so the factors that can be identified are limited by the type of images. For example, training Google Maps images cannot give information about whether buildings are factors associated with cyclist crashes, because buildings are not shown in Google Maps images in the training datasets. This paper identified factors related to infrastructure characteristics. Cyclists characteristics such as gender and age [19] that are not in the images cannot be identified by this method.

Another limitation of this method is the incompleteness of the dataset, especially the crash data and exposure data. The officially reported number of crashes can be significantly lower than the actual number of crashes [20]. The exposure data does not cover all the trips. The incomplete record of crashes and exposure provides a generic indication upon where the crashes and trips are more and where are less, therefore the data can still be used for training purposes. There is still potential that the incompleteness of the records leads to biased training results. A complete record of the crashes and exposure will lead to more accurate outcomes. However, high-quality exposure data is difficult to obtain [21]. Appropriate exposure measurements and crash measurements are fundamental questions to be addressed [22].

16.5 Conclusion

This paper presents a deep learning method to model road environments and identify factors that are associated with cycling crashes. The factors include tram tracks, on-street parking, intersections, on-road bicycle lanes, median strips and green spaces. The method has been validated by an experiment that identifies factors as anticipated. The results confirm that factors associated with bicycle crashes can be identified by modelling and comparing streetscape imagery for crash and non-crash domains using GANs. This paper contributes to the literature by providing an analytic tool to assess the road environments and cyclist crashes. The method provides insights to urban designers, infrastructure planners and cyclist towards how to improve cycling safety and prevent crashes. Since images data such as Google Maps and satellite images are available worldwide, the method can be readily applied to any other country and region.

The method identifies factors associated with cyclist crashes by analysing imagery of urban areas. The advantage of this method is that it is not limited to one or two factors, rather it explores all potential factors that may be associated with bicycle crashes. The main limit to the range of factors it can explore is the amount of information the images provided. The method is purely based on objective imagery information; therefore, it eliminates the possible bias in traditional human participated research methods. The method is not limited to bicycle safety, and can readily be applied to other research domains such as pedestrian safety and vehicle safety. Due to the limited information provided by satellite images and Google Maps, the factors identified in this paper are mainly related to the urban infrastructure and urban environment.

Exposure and crash data are the key factors that may affect the training results. The exposure data may not cover all real trips, and the number of crashes is often underreported. The availability of a complete dataset will improve the accuracy of the results. Future work can also incorporate other data sources such as vehicle volumes, and train images from other sources such as Google Street View images or maps containing traffic information. Future research may investigate other modes such as pedestrian safety and vehicle safety, and focus on specific types of infrastructure only such as intersections and roundabouts.

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