Usage of street-level imagery for city-wide graffiti mapping

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ABSTRACT The graffiti drawing acts when performed in unauthorized ways are generally considered as vandalism crimes. A valuable tool for public authorities in the combat of such acts is a map of the concentration of occurrences of graffiti of a region if one consider the Broken Windows theory [1]. Currently, obtaining such concentration map is expensive because it require in-person auditing of the whole region. In this work we propose an automatic way of obtaining such a map using ground-level images and machine learning and validate it using images from a city known to have high concentration of graffiti – São Paulo, Brazil. An extended version of this work has been published in [2]. The first author was born in São Paulo and is currently pursuing his PhD degree at USP. He was involved in all steps of this work, particularly in the method proposal and implementation.

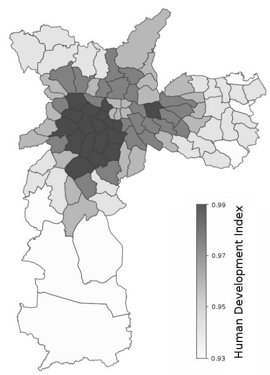
INTRODUCTION Graffiti is generally considered part of the Urban Art movement, despite its controversy acceptance. The graffiti drawings can be grouped into at least two types: *artistic drawings* and *tagging* (or *bombing*). Tagging is generally performed without the consent of the owner and as such it is generally simpler and mainly composed of words and symbols. In this work, by graffiti we will be referring to this kind of drawing. There are several works that apply ML in an attempt to combat graffiti [3]–[11], but none have proposed a way that allowed one to measure the *level* of graffiti in a location. In this work we propose a method to obtain the graffiti map of a region in an automatic way using ground-level images and ML techniques for identification of graffiti. We apply such method in São Paulo, Brazil to obtain a graffiti map of the city.

PROPOSED METHOD The method consists of three steps: image acquisition, training of the graffiti learning model and the graffiti map computation per-se. Initially the region of interest is defined, considering the ground-level images coverage of it. We assume a 360 degrees view from each location. Images are acquired in a systematic way [12] and a sample of it is manually annotated regarding the regions affected by graffiti and used to train a discriminative model. This task could be formulated as a classification problem, which would give us an imprecise information of each location. It could also be formulated as a detection problem, which would give us more detailed information about the regions affected by graffiti. And also, it could be formulated as a regression problem, which would give us a numerical value for each image, corresponding to amount of the image affected by graffiti. Thus, we defined the graffiti level $f(P)$ of a location P as the area in the images of that location affected by graffiti. In case we want to obtain a 2d histogram g that measures the relative concentration of graffiti in a pre-defined regions, we finally define the graffiti level $g(R)$ of a region R as the average of the graffiti levels of all points P_j inside that region.

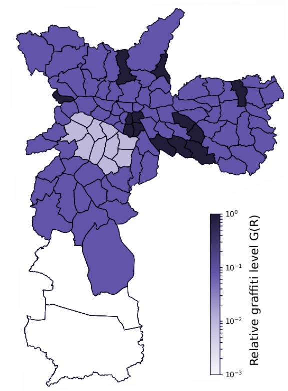
$$g(R) = \frac{1}{n}\sum_{j=1}^{n} f(P_j) \tag{1}$$

EXPERIMENTS We validate the proposed method using Google Maps street-view images [13] and a Mask-RCNN [14] segmentation model to obtain the graffiti mapping of São Paulo. A regular square grid of 102m spacing of points in the same line of latitude or longitude is initially created over the extent of São Paulo. For each point in the grid, four images with 90 degrees disjoint views were obtained. It resulted in 68,752 points in the city and 275,339 images. A total of 632 images were sampled and manually annotated. A COCO dataset pre-trained model of the Mask-RCNN was used to finetune a 101-layers residual model. A momentum of 0.9 and a fixed learning rate of 0.001 was utilized to train the model for 80 epochs to obtain a graffiti model with 0.64 of average precision, using the VOC 2007 segmentation evaluation metric. Figure 1c presents the final graffiti level histogram of the city. It can be noticed that there are regions of high concentration of graffiti while others present no or just little presence of it. Given the public nonexistence of graffiti levels histograms to our knowledge, there are no direct ways to validate our results. For this task, we cross-referenced our results with the Human Development Index (HDI) provided by the city hall. There is no direct or inverse correspondence of the regions between the two maps, but it can be seen that regions with lowest occurrences of graffiti have the highest HDI.

(a) Graffiti identification



(b) HDI



(c) Graffiti level map

Fig. 1: (a) Sample of the evaluation by the graffiti segmentation model. (b) HDI from São Paulo districts in 2007 [15]. (c) Relative graffiti level histogram of São Paulo city using the proposed approach. The divisions represent the city districts and the colors in logarithmic scale express the relative graffiti level clustered in five levels, according to Equation 1. The two bottommost districts were not considered given the unavailability of data in the region.

CONCLUSIONS This work proposed the first attempt to our knowledge to compute the graffiti level histogram of a city without the requirement of in-person auditing. Ground-level images are systematically collected, the discriminative model is trained and used to evaluate the occurrences of graffiti in the region of interest. We validated our approach using Google Maps [13] street view images and a Mask R-CNN [14] segmentation model to obtain a São Paulo graffiti level histogram map. It was cross-referenced with the HDI of the neighbourhoods and showed the association of rich regions with low occurrences of graffiti. Future works includes the refinement of segmentation model, novel ways of validating our final histograms and the use of new datasets.

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