Detection of Informal Graveyards in Lima using Fully Convolutional Network with VHR Images

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***Abstract*— Lima is facing rapid urban growth, including a rapid expansion of informal areas, mainly taking place within three peripheral cones. Most of the studies on that subject focused in general on informal settlements. Yet in this paper, we focus on two different informal types, graveyards and housing. They are experiencing complex, intertwined development dynamics due to a lack of land for housing and burials, causing social and public health problems. Housing invasions on burial grounds have never been systematically investigated. Yet, while challenging due to their morphological similarity, the detection of boundaries between graveyards and neighbouring and sometimes invading informal housing is essential, e.g., to prevent the spread of diseases. This study aims to distinguish those similar urban structures of which the visual features are very alike (e.g., rectangular shapes, same colours, organic organization). We used state-of-the-art Fully Convolutional Networks (FCNs) with dilated convolution of increasing spatial kernels to acquire features of deep level of abstraction on Pleiades satellites images. We found that such neural networks can reach a good level in mapping both informal developments with a F1-score of 0.819. Effective monitoring of such developments is important to inform planning and decision-making processes to allow interventions at critical locations.**

Keywords*— Fully Convolutional Networks (FCNs); deep learning; urban remote sensing; barriadas; informal settlements; informal graveyards; Lima.

I. INTRODUCTION

Lima, the capital of Peru, faces rapid urban growth, including the expansion of informal areas[1]. The growth of informal neighbourhoods, so-called *barriadas*, has historically been part of the urban development [2], [3] and tends to take place in three peripheral cones [4]. Some of the places that were barriadas a decade ago are now relatively well developed and formalized areas [4]. After the rural exodus of the twentieth century, new barriadas were created for demographic reasons, they appeared on pockets of empty land close to consolidated areas. Local urban planning departments have not been able to control these land invasions. As part of this informal and uncontrolled urban development, informal graveyards appeared next to informal settlements due to a lack of formal cemeteries for low-income groups [5]. Later, several graveyards were formalized, but due to a lack of affordable land both for housing and for burial, new informalities appeared. These intertwined development dynamics of informal settlements and graveyards must be under strict surveillance since graveyards can challenge public health, e.g., when mosquitos responsible for the spread of diseases such as the Zika virus cannot be properly controlled. The Peruvian law states that cemeteries need to be physically separated by a high wall and a 2 meters fringe from the surroundings to avoid infringements [6]. For that reason, the Peruvian Ministry of Health has tried to make an inventory of all graveyards in Metropolitan Lima [7], but this list is incomplete and land invasions occur at a higher pace than state institutions can respond to. Although of high societal importance, land invasions on burials grounds have never been systematically investigated. This study addresses this gap through a remote-sensing based advanced machine learning approach.

Among the present remote-sensing based studies to detect informal settlements, Fully Convolutional Networks (FCNs) [8], [9] showed an excellent capability to streamline the classification workflow by merging the spatial feature extraction and the supervised classification into one single framework, generally resulting in higher classification accuracy. FCNs [10] are neural networks designed to perform pixel-wise image classification. Even between classes with close semantic features, the accuracy assessment proved that FCNs can distinguish informal from formal areas [8], [11]. Yet, whether it was with FCNs or with other machine learning methods, this distinction is commonly made in a binary way [11], [12], [13], ignoring differences within informal areas. Informal areas, although morphologically similar, are very diverse [14]. Nevertheless, the capability of FCNs to distinguish informal neighbourhoods and graveyards, which are semantically close classes, has not been explored. These two classes share similar spatial and spectral features, e.g., the tombs are protected from the sun by metal sheets like some informal houses or tombs are stacked together in larger structures like houses made of bricks. This makes them difficult to distinguish by a birds' eye view.

In remote sensing literature, graveyards have been investigated, mostly motivated by two purposes, i.e., archaeological studies and crime detection. For archaeology, remote sensing is an efficient, non-destructive technique to find ancient cemeteries [15], [16], mainly focusing on the preservation of the archaeological patrimony [17], [18]. For the fight against crime purposes, remote sensing allows to find clandestine burials of victims of crime [19], [20], especially using infrared (IR) or near-infrared (NIR) spectral

Fig.1 Ground photos of tombs (right) and informal houses (left) (upper left and middle) credit to Christien Klaufus; Pleiades image of tombs (East) and informal house (West) (lower left) and map of the selected areas (right).

bands. Yet the developed techniques are meant to be used shortly after the burial. Remote sensing could be an effective tool for the detection of graveyards, but to the best of our knowledge, it has not yet been systematically investigated for this purpose. Therefore, the aim of our study is to distinguish these two similar types of informal settlements employing deep-learning methods. We opt for deep-learning methods due to the encouraging results of earlier very high resolution (VHR) image classification studies [19], [20],[23] and informal settlement mapping studies [8],[24]. The study uses Lima as a case, however, the developed methodology has application potential for similar urban development processes, e.g., Manila (Philippines) or Cairo (Egypt).

II. Experiments

A. Dataset

The dataset is composed of a set of both panchromatic and multispectral Pleiades images (Fig. 1). The scenes were acquired for two different areas: Villa Maria del Triunfo (VMT) with an area of approximately 100 km^2, located South-East of the historical centre of Lima bordered by a mountain with a large graveyard on its slope; and San Juan de Lurigancho (SLJ) approximatively 200 km^2, a more recently developed district in the North of Lima with peripheral areas consisting of informal settlements growing on steep mountainsides surrounding the district. For both areas, we acquired cloud-free images for two different years (2013 and 2016). The scenes were taken on February 2013 and 27th of March 2016 for SLJ and on the 13th of April 2013 and on the 2nd of January 2016 for VMT.

B. Methodology

The methodology consists of five steps (Fig. 2). First, pan-sharpening the scenes reduced the number of input images for the FCN's to six (three dates of acquisition across the two zones). The resolution of those pansharpened images is 50cm. Second, we chose areas that suited our training purposes. We selected 10 areas for the experiments (Fig. 1). The areas are squares of 1000 by 1000 pixels, fulfilling the following two criteria: 1) an area contains at least two different types of designated urban structures; 2) scenes within areas should, when possible, overlap to have a variated panel of spectral responses for our classes. Five areas were chosen in SLJ and five in VMT (Tab. I). Eight tiles were unusable or inexistent (contained in areas where the scenes did not overlap). Thus, we managed to get 22 usable tiles of 1000 by 1000 pixels. We divided this set of 22 tiles into test and training test. They were 13 training tiles and 9 testing tiles. We split the total set so that the FCN will train as few as possible on the same area to prevent overfitting. The third step involved mapping the two urban structure types of interest, i.e., the graveyards and informal settlements. To do so, we also added other classes (i.e., formal settlements and non-built areas) such that the neural network would learn to detect all classes. As this semantic distinction did not exist in the reference data, we created it ourselves by using land use maps of Lima, expert knowledge of a sociologist working on Lima, the latest census data (2007), and photo interpretation.

We used the following criteria to create the ground-truth by photo-interpretation:

- *Formal settlements:* The area should be at least 500m² being part of a grid system, served by formal roads made of asphalt and at least partially on the latest land use maps we had of Lima (Note: the map is from 2007, and land use may have changed since).
- *Informal housing*: The area should be at least 200m², being composed of two or more buildings. Those buildings must show an organic pattern, clearly distinguishable from the grid pattern of planned areas. The area should be served by a section of a mud road or no road at all.
- *Graveyards*: the area should be at least 2,500m², can or not appear on formal maps (the current mapping of the graveyards is incomplete) and are indicated by our expert.
- *Non-build areas*: The area should be at least 15,000m² and should neither have any building on the maps nor any distinguishable building on the Pleiades' images.

TABLE I. Division of ground truth's classes according to the areas.

Classes	Area Number									
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Formal settlements	X	X	X	X	X	X		X	X	X
Informal neighbourhoods	X	X	X	X	X	X	X	X	X	
Graveyards			X		X		X	X		
Non-built areas	X	X	X	X	X	X	X	X	X	X

Fourth, the training of the neural network was conducted on 10 areas of interest within five scenes acquired by Pleiades satellites. We extracted tiles within the areas from the different scenes. Extracting both scenes of 2013 and 2016 allows to have a wider sample of graveyards and informal settlements. The differences of angle between a scene of 2013 and a scene of 2016 of the same area provide a larger diversity of spectral responses for those classes. As said previously, from the 10 areas selected across the scenes, 22 tiles were extracted and used. We delineated the different classes in those tiles, following the criteria above. Then, we divided this set in 13 training tiles and 9 testing tiles. Thus, we tested the predictions of our neural network on a dataset which was independent of the training dataset. The neural network trained was a Fully Convolutional Network with a Dilated Kernel [8]. The particularity of an FCN using dilated kernels of convolution is that the receptive field will increase exponentially with the depth of the network. This is very pertinent for extremely large images such as VHR images. For the classification, we experimented with different structures of those neural network, with a depth of 3 to 6 layers. The final network that we selected, trained and used, had six layers (FCN-DK6). The training was processed using back propagation of a stochastic gradient. We have the FCN trained on 500 (being the number of samples within a tile) ×13 (being the number of training tiles) random samples using patch size of 125 pixels, with two different learning rates for 300 epochs following [8]. The first learning rate of 10^{-4} was used for 280 epochs. For the 20 epochs left, we used a learning rate of 10^{-5}. The first learning rate reduced the training error but had an unstable behaviour on the error on the validation set as a drawback. The second one stabilized both training and validation error.

Fifth and last, as results, the trained network (FCN-DK6) allowed to produce labelled images. The accuracy was evaluated using the F1-score (UA: User Accuracy and PA: Producer Accuracy):

$$F1 = \frac{2 \cdot UA \cdot PA}{UA + PA}$$

III. RESULT

A. Outputs

After having the neural network trained on the training dataset, we used it to predict the classes of the test tiles (Fig. 3).

Fig. 3 Pleiades image (left) Manual delineation (middle) FCN prediction (right) – (TE3 e.g.).

We then compared the manually delineated tiles to the automatically predicted ones to assess the accuracy of the prediction using F1-score. Visually, the results show that the FCN was both accurate and capable of finding small pockets of informal settlements that were not delineated in the ground-truth because of our criteria (section II.B). Quantitatively, the global F1-score reached 0.819 with the DK6 (Tab. II). The first experiments were led with an FCN with a depth of 3 (FCN-DK3) neural network. The more we added depth to the neural network, the higher was the accuracy. That is why we chose to use the FCN-DK6. However, the additional layers were computationally costlier for the training. Since our large training dataset was particularly time-consuming to train on, we limited ourselves to 6 layers (Fig. 4).

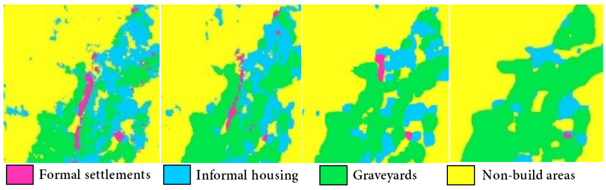

Fig. 4 Outputs on the same Pleiade image with FCN-DK3 (left) to FCN-DK6 (right).

The networks considered here are implemented using the MatConvNet library version 1.0-beta-23 compiled with CUDA-8 toolkit and cuDNN support.1. All experiments were performed on a desktop workstation with an Intel Xeon CPU E5-2643 at 3.4 GHz, 128 GB of RAM, and a Dual Nvidia Quadro K2200 GPU.

TABLE II. Accuracy from the testing set and training time according to the depth of the neural network applied.

Network	**FCN-DK3**		**FCN-DK4**	
	F1-Score	*Producer accuracy*	*F1-Score*	*Producer accuracy*
Formal settlements	0.798	0.824	0.821	0.851
Informal housing	0.542	0.530	0.596	0.578
Graveyards	0.652	0.620	0.779	0.750
Non-built areas	0.863	0.857	0.886	0.877
Global F1-Score	0.714		0.770	
Training time	1 hour		6 hours	
Network	**FCN-DK5**		**FCN-DK6**	
	F1-Score	*Producer accuracy*	*F1-Score*	*Producer accuracy*
Formal settlements	0.827	0.875	0.859	0.871
Informal housing	0.594	0.520	0.688	0.660
Graveyards	0.825	0.773	0.840	0.882
Non-built areas	0.884	0.907	0.888	0.880
Global F1-Score	0.782		0.819	
Training time	24 hours		72 hours	

Our study aimed to distinguish graveyards and informal housing. Therefore, we also trained it on formal areas and non-build areas. The F1-scores reached for those classes within the testing set are 0.840 (graveyards) and 0.688 (informal housing), respectively. The F1-score of the informal housing is lower compared to the others, because the delineation of informal settlements is more uncertain [25]. Thus, the training data used for this class is the most subjective one.

B. Discussion

The aim of our study was to evaluate the use of FCNs to distinguish graveyards and informal housing. Therefore, we trained the FCN on areas with graveyards and informal settlements. Such areas also host other types of land use such as formal buildings and non-built area. Hence, we also included those types in the training. However, by doing so, we added uncertainties in the training due to the delineations. The confusion between delineating informal settlements and formal is a common problem [25]. It can lead to miss-classifying formal and informal areas. Due to the high uncertainties, it might be an option to aggregate the two classes of residential settlements (formal and informal housing) posteriori of the classification (Tab. III).

TABLE III. ACCURACY BY MERGING THE CLASSES "FORMAL HOUSING" AND "INFORMAL HOUSING" INTO "RESIDENTIAL AREA"

Class	Residential area	Graveyards	Non-built areas
F1-Score	0.907	0.839	0.888

IV. CONCLUSION

Informal settlements are part of the growth of Lima. Due to a high pressure on land, new settlers are seeking for the easiest to access areas to build houses on. Due to the available spaces inside and around the graveyards, they settle there. Those informal settlements and the tombs in Peru share a similar appearance from a bird's eye view and are hard to distinguish. However, the FCNs we trained can distinguish these two types of structures. The dilated kernels of our FCNs allowed the neural network to integrate contextual features to the training without being too demanding in term of computational costs compared to regular CCNs. The deeper our FCN was, the higher was the accuracy. However, this depth came with higher computational costs on the training of the network. Nonetheless, we argue for a deep network, as once the training is processed, the prediction is by far quicker. The methodology we developed and the neural network we trained distinguished the graveyards and areas where people live with high accuracy. Future developments could focus on using this neural network to monitor temporal dynamics of the borders between graveyards and living areas comparing the scenes from 2013 and 2016. Upscaling the developed FCN algorithm to a larger area or other areas can inform the planning and decision-making process in those places but requires a considerable coverage of VHR imagery and up-to-date, consistent training data.

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