Data task for the AHP data scientist position

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1 Problem and approach

The goal of this empirical exercise is to detect land surface change over 80 years in the San Francisco area using two photographs of the same place, one panchromatic aerial image taken in 1939 and a satellite image taken in 2019 with only the RGB spectral bands. The assignment is fairly abstract, and our resources limited. We therefore focus on the particular case at hand, that is, pictures that are showing us either urban residential areas and roads or agricultural cropped areas. From this perspective, these two images indicate a long term evolution of the land cover from agricultural to urban. We are therefore interested in graphically defining and detecting this change with an approach that could be reused with photographs of the same type showing similar areas. Detecting this change means that we need to determine in each image which pixel belongs to an agricultural surface and which pixel does not. This is an image classification problem.

First of all, we simplify the problem by harmonizing the spectral dimension of the two images. It seems that the first image was taken with a sensor that is sensitive to the entire wavelength interval of visible light, so we have a black and white picture [1]. In order to use the intensity of tone as an information in the older image to be compared to the new image, we convert the recent picture to the gray scale. We compute a conventional 'luma' linear combination of the red, green and blue intensities to obtain gray tones [2]. We do the same for the older photograph because there are a few pixels with very small differences across the three bands.

There are as of today many existing methods to classify images. State of the art models, notably used in remote sensing applied to social sciences rely on convolutional neural networks Jean et al. [2016]. With this approach, we would need to collect images for our specific purpose, that is, with a similar spatial and spectral resolution, showing similar areas and that already have the areas classified as urban or agricultural. We would use a part of this sample to train a computer vision model, the other part of this sample to validate the model, and once the final calibration of the model is obtained we would predict the labels of the two old and new photographs of the assignment. Nevertheless, for two reasons we opt for a simpler approach : first we do not have labelled sample images and collecting them is time consuming. Second, we cannot rely on methods used for multi spectral images given the black and white old photograph, so the method we choose will solely rely on the variation of the gray tones across the pixels of our photos.

Texture analysis is an older but still conventional method to classify images including aerial and satellite images when their spatial resolution[3] is sufficient (Kupidura [2019], Haralick et al. [1973]), but it is also applied to other domains, in particular medical imagery (Castellano et al. [2004]). It is particularly adapted to the case of gray scale images as it intends to describe the variability in tones of a single band.

One widely used texture analysis method of panchromatic images is the 'co-occurence matrix' method (or *grey level co occurence matrix*, GLCM) first presented and used in the case of satellite images by Haralick et al. [1973]. Given a matrix representing the gray tone of each pixel in all the sub-parts of an image, the idea is to compute how often pairs of pixels with a specific tone and offset (how far apart they are from each other and with what direction) occur in this sub-part.

[1] reading it in R gives us the three RGB bands, but almost all pixels have equal values for the three bands and when that is not the case, the difference is of course very small

[2] The coefficients are respectively 0.3, 0.59, 0.11

[3] we searched on Google Earth where the images came from so as to have an idea of the spatial resolution. It seems that a pixel is about 7 by 7 meters which is a relatively high resolution

There are as many rows and columns in the underlying matrix as there are existing tone values in the image, and each entry is a count of co-occurrence for a given offset. Once that matrix is obtained, one can compute various statistics that aim to represent the local distribution of tones.

Urban areas are usually characterized by a locally coarse texture as opposed to the smooth texture of agricultural and forest areas (Ferro and Warner [2002]). If we look at our modern photograph converted to black and white, it is quite remarkable. We will make use of this pattern and use as a statistic from the GLCM the 'contrast':

$$\sum_{i,j}(i-j)^2 p(i,j) \tag{1}$$

where i and j are the matrix cell index, $p(i,j)$ the underlying frequency. This statistic is a measure of the intensity contrast between a pixel and its neighbor.

Once we obtained the contrast images for each of the two photographs, we will inspect them visually to see how contrast correlated with the residential area or agricultural land presence and will formally classify the images using a simple unsupervised classification technique. The final products will be the classified counterpart of the two images.

2 Implementation

We implement our approach through the following steps :

1. convert both images to grayscale using a simple linear combination of the three bands
2. compute the GLCM matrix and the contrast statistic for both images and plot the resulting contrast images for visual inspection
3. implement a simple k-mean clustering unsupervised classification searching for two clusters (agricultural land, urban residential area and roads) in the two images.
4. plot against each other the panchromatic images, contrast images and classified images to evaluate the approach and the magnitude of the land cover change it is able to detect.

When implementing texture analysis with the GLCM approach, one has, except the statistic, two important parameters to choose : following examples in the literature and visual inspections of how different values of the parameters were performing, we chose as a window size 7 by 7 pixels and as directions for the offsets all the possible horizontal and vertical directions with a distance of one pixel.

Once the contrast matrix images are obtained, we classify each pixel using the k-mean clustering algorithm with $k = 2$.

3 Results

Below we display a panel of 2×3 figures : the two panchromatic-converted photographs, the two contrast images, and the two classified images.

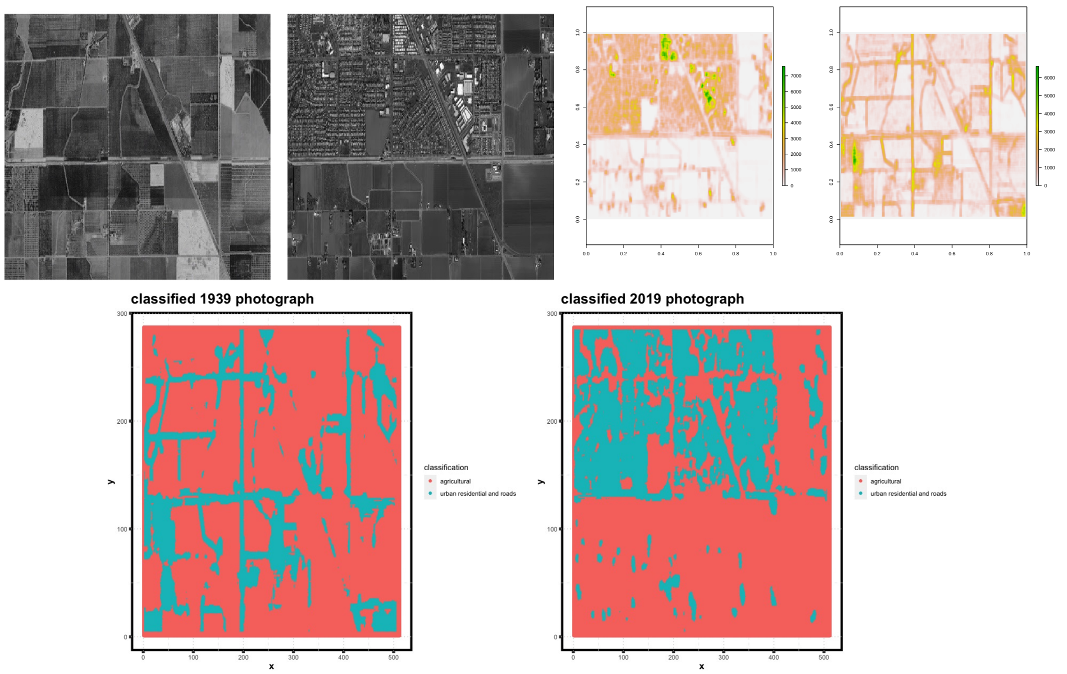

Figure 1: The two panchromatic photographs (1-2), their contrast images counterpart using GLCM matrices (3-4) and the contrast images classified using k-mean clustering (5-6)

Given the classified map, one could easily compute the long run change in urbanized land cover surface or equivalently the change in agricultural land cover surface.

Given the graphical results, we highlight here the strengths and the limits of this method, as well as possible developments and alternatives

- because the residential area exhibits a lot of local coarse variation, there is a strong correlation between the contrast value and the residential area location and the roads. Therefore, in the modern image, the model is good at identifying and separating the urbanized area versus the homogeneous, agricultural area.

- the model is less good regarding the older image. Although the patterns of the roads are clearly identified, they are too thick, and substantial agricultural areas are labelled as urban residential or road. There is much more gray tone variation within the agricultural areas in the old picture versus the first : in particular, the cropped areas with pixel to pixel large variations (such as the bottom left part of the old image) are labelled as urban because of this.

- our method is computationally acceptable. It takes one minute for the matrix to be computed for each image, with a single-process on a laptop. If we were to use this method with a million images rather than two, it would not be possible to run this locally though and one would have to use distributed computing, in an external server or on the cloud. The library 'parallel' in R is a simple and user friendly tool to distribute across a number of CPUs the execution of a function across an array of input parameters. We could use it for the task of computing the matrices. In order to do so we would re-write the code in a functional way, having a function for the matrix computation and a function for the classification. One problem with R though is that it loads most of its data into memory and very large datasets become complicated to handle. An alternative is to perform the same analysis in python using xarray and Dask.

- our method is very simple and aims at broadly identifying urban versus agricultural areas in photographs of this very specific type. This method isn't very generalizable – it would not perform well if we were for example given a countryside image with small hills and altitude variation which would mean enough contrast for it to be identified as urban. With more time, we could in addition allow for morphological distinction in the model. Alternatively we could spend the time to collect labelled training data and implement a computer vision machine learning model.

References

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