Differential image analysis using Shannon’s entropy: preliminary results

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Abstract. Image analysis is a well-researched area, although some open problems have still to be addressed. Deserving further investigation, we consider the problem of detecting natural or artificial areas in images. This paper describes the initial research towards this goal, based on Shannon’s concept of entropy of information, as a mean to allow the detection of areas that are more irregular and thus, probably natural, or more regular, and thus probably artificial. This paper also describes the limitations of this research, and points out future research problems regarding the automatic identification of artificial and natural zones in an image.

Keywords: Image analysis, Shannon Entropy.

1 Introduction

The detection of natural and artificial areas in an image is an interesting problem from different points of view. For example, if a system can automatically detect an artificial zone in an image, it can try to overlay relevant information for the user, in a seamless manner, in that particular zone. Another type of application refers to the detection of areas that are artificial or natural in surveillance videos, allowing this detection to be further used in Ambient Assisted Living (AAL) tools, e.g. in the monitoring of home environments.

Shannon’s entropy [1] is often referred to as a tool to assess the level of information that is present in a set of data, being higher when the level of information is high, and zero when the set of data carries no information at all. The use of Shannon’s entropy to analyse data has been applied in many fields, including image analysis (e.g. [2]), but it’s not the goal of this paper to present a thorough state of the art on this field. In the
last section, the interested reader can find a short but selected set of suitable references that cover the use of entropy and other methods for data analysis.

The rationale to use Shannon’s Entropy to assess areas in images that are natural or artificial is primarily related to the level of homogeneity or heterogeneity of colours in artificial or natural zones in an image. i.e., the more heterogeneous an area in an image is, the more likely it is a natural area, and inversely, the more homogeneous an area is, the more likely this area is artificial.

As Shannon’s Entropy is applicable to a linear set of data, and pictures are bi-dimensional data, often with each point being associated with information on a representation of the colour, this paper also describes the approach to assess Shannon’s entropy in an image.

Yet, there are a number of limitations for this approach, for example, if we consider a picture of a clear or grey sky or of a lake or calm sea, it is immediately perceived that there will probably be large areas where there is very little variation for the colours and contours of the objects, therefore rendering this approach completely ineffective. Therefore, the paper also discusses what are the limitations of this approach.

The remainder of this paper is organised as follows. Section I, Introduction, is concluded with this paragraph. Section II describes the concept of Shannon’s Entropy, and describes how the assessment of this measure is transposed from a linear set of data to a bi-dimensional set with colour point information. Section III presents some of the results and Section IV concludes the paper, presenting a small set of meaningful references for further enlightenment of the interested reader, and possible future research directions on this field. Acknowledgements and References complete the paper.

2 Image analysis and Shannon’s entropy

Shannon’s entropy was first presented in the 40’s of the last century, and has been extensively used not only in its original field of creation, information theory for tele-communications, but in very diverse areas of science. Entropy is a concept that has its roots in the scientific area of Thermodynamics, and is central to the famous Second Law of Thermodynamics, that states that in a natural thermodynamic process, there is an increase in the overall entropy for all the involved systems. This means that when a process occurs, the available energy to be applied to realize work, enthalpy, decreases because the systems are inherently inefficient and there is energy that is not usable and therefore wasted (as not used for useful work), being this energy responsible for the increase of entropy. Entropy has also been used, since Shannon, to measure the degree of information potentially available in a set of data, i.e., the more information the data has, the more entropic that data is. In fact, entropy also stands for disorganization, and it helps to understand why a large set of data is more likely to be disorganized. On the contrary, if a set of data is small or contains only the same piece of information, the entropy of that set is zero.

Shannon’s Entropy is usually represented as show in expression (1):

$$- \sum_{i=1}^{N} P(x_i) \log(P(x_i))$$

(1)
In (1), \( N \) is the size of the set of data composed by all \( x_i \), and \( P(x_i) \) is the relative probability for \( x_i \) to occur within that set. As an example, if we consider the set \{1,2,3,4,5\} each element has a relative probability of 1/5 and Shannon’s entropy for this set would be \(-5 \cdot \frac{1}{5} \log\left(\frac{1}{5}\right)\), i.e., 0.6989, while if the set was to be composed of only the same element, say \{1,1,1,1,1\}, its Shannon’s entropy would be \(-5 \cdot 1 \cdot \log(1)\), i.e., 0, because \( \log(1) = 0 \).

Images are sets of data in which each point of the image has associated information that represents the colour of that point. Each of this set of values, finally, can be represented as Hue, Saturation and Value (HSV) or Red, Green and Blue (RGB).

A colour space is a measuring system for colours that can be perceived by humans [3]. RGB colour space is the most commonly used colour space in displaying colour devices. RGB colour space is an additive space that uses the three primitive colours: red, green and blue. These colours are then combined in order to reproduce all the colours of the RGB colour space. Although RGB is a good colour space for colour displaying, it is not however efficient in image processing operations, such as colour segmentation and analysis, largely because of the correlation between the R, G and B components [4]. For example, when a colour changes, all three components will also change. Nevertheless, as we are precisely looking for changes in the colours, the images are interpreted in the RGB format.

To apply Shannon’s entropy to a multidimensional set of data such as the data in a picture is different challenge. Firstly, we need to consider that an image is a bi-dimensional matrix in which each point carries information regarding the colour of that point. Moreover, as we are looking for changes in the colours of in a zone of the image, it makes little sense to measure the entropy of a given colour channel for the whole image. Having these restrictions into consideration, it was defined that:

1. the set of data to be measured would consist in a square of vicinity of 3, 5 or 11, meaning that the points to evaluated will be the square of points centred in the pixel at analysis, with dimension of 9, 25 or 121 pixels;
2. this square will sweep the image, each point of the image being the centre value for the assessment;
3. the entropy is measured separately for the Red, Green and Blue channels for each pixel;
4. as the value of the entropy is a real number between 0 and \( \log(1/n) \) where \( n \) is the size of the sample, in order to be represented as an image again, the value of the entropy for each channel is finally normalized between 0 and 255.

Additionally, it was considered that the system should be able to disregard minor changes in the value of the colour channel, i.e., using the equation (1), a value of say 171 and 170 were regarded as different as the values 0 and 255. With the application of a rounding pre-processing, the values would be rounded to the next order of magnitude, i.e., all the values between, e.g., 170 and 179 would be represented as 170 and so on.
Also, a procedure of normalization of the values was tested, where the weight of each colour channel was normalized to include the sum of all the channels in the pixel, i.e., for the channel Red, it would be used the value

\[ R' = \frac{R}{R + G + B} \]  

and so on.

Finally, it was also experimented to pre-process the image with several filters from the Aforge software [5], including a Gaussian filter, a HSL filter, a linear HSL filter and a Hue filter.

Figure 1 (a), (b) and (c) show how the algorithm considers the vicinity of pixels in successive iterations. The area in yellow and orange marks the pixels that are considered to contribute to the calculation of the Shannon’s entropy for the pixel marked in orange.

![Fig. 1. Evolution of the calculation of a 3x3 box for the entropy of the central pixel marked in orange (value 15 for iteration n, value 17 for iteration n+1, and value 160 for iteration n+2).](image)

### 3 Results

As detailed in Section II, the calculation of the entropy of each pixel is thus the calculation of the entropy of the set of data for each channel for all the pixels in the vicinity of that particular pixel, as shown in Figure 1 (a), (b) and (c), considering a vicinity of 3.

For these experiments, three images were used, as seen in Figures 2, 3 and 4. These images include two indoor environments and one outdoor environment. The pictures were sampled to be 160*120 pixels for image 2 and 4, and 320*240 for image 3, i.e., low and very low resolution images. Image in Figure 2 is a high contrast image that shows two persons sitting and standing in an office, with large windows facing a building and a piece of sky. Image in Figure 3 shows two of the authors and a friend standing and sitting in the same office, with very uneven lighting. Image in Figure 4 shows outdoor urban scenery, with a road, some cars, a tree and a person far away. Only one off-the-shelf webcam was used.
To these images were applied the set of algorithms and filters presented in Section II, with the results that can be observed in the following figures, described with more detail.

The larger the vicinity, the more blurred the result of the entropy, because there will more influence of the neighbour values. Figures 5 (a), (b), and (c) show the result for the application of the vicinity of 3, 5 and 11, respectively for the image in Figure 2.

It is clear that the larger the size of the data set for the calculation of Shannon’s entropy for each pixel, i.e., the larger the vicinity that integrates the data set that will feed the entropy calculation algorithm, the less sharp the edges of the shapes are, because more elements contribute to dilute single and sharp changes in the values of the pixels.
which have, expectedly, little information and therefore have similar entropy values. This is an interesting result to be considered when investigating the adoption of Shannon’s Entropy in image analysis for AAL, where the primary objective of any analysis is to recognize and monitor users in living environments.

Fig. 6. Image showing the application of the initial Shannon’s entropy algorithm for vicinities of 5 for the image in Fig. 2.

Fig. 7. Image showing the application of the initial Shannon’s entropy algorithm for vicinities of 11 for the image in Fig. 2.

Fig. 8. Result of the application of algorithm for Shannon’s entropy for the image in Fig. 3, vicinity of 3.

Fig. 9. Result of the application of algorithm for Shannon’s entropy for the image in Fig. 4, vicinity of 3.

Figures 6 and 7 show the application of the same algorithm to the images in Figures 3 and 4 with a vicinity of 3.

As it can be perceived by the visual analysis of Figures 6 and 7, there is not a clear hint on where the non-artificial elements are on both pictures, except that the natural elements are almost always shown with a touch of green, including the tree in the less informative image from Figure 4.

The application of the rounding to the values of the colour channels resulted in the images shown in Figures 8, 9 and 10. We propose that the analysis of these images is
subject to more study, as, on Figure 8, it is clear that the black areas indicate natural elements, but that criterion does not hold for images in Figures 9 and 10.

The curvilinear artefacts that can be observed in Figure 8 and 9, as curves in red, white and green, and only in white in Fig. 10, may possibly be explained as a limitation of the webcam that was used, and therefore, more research is necessary.

Applying the normalization of each colour channel as described in equation (2) results in the images shown in Figures 11, 12 and 13. It can be seen that the natural elements are show in non-black, except for the image from Fig. 4, which includes coloured parts for artificial elements, e.g., the contours of the car that is shown in the lower right part of the image.

Fig. 10. Result of the application of algorithm for Shannon’s entropy for the image in Fig. 2, with a rounding to the tens of each colour channel.

Fig. 11. Result of the application of algorithm for Shannon’s entropy for the image in Fig. 3, with a rounding to the tens of each colour channel.

Fig. 12. Result of the application of algorithm for Shannon’s entropy for the image in Fig. 4, with a rounding to the tens of each colour channel.

Fig. 13. Result of the application of algorithm for Shannon’s entropy for the image in Fig. 2, with normalized values for each colour channel.
The application of the filters from the Aforge software resulted in the elimination of some artefacts from the images, as seen in Figures 14, 15, 16, and 17, all referring to the image from Fig. 2. It is also to be considered as future research the addition of these filters to the other algorithms. Nevertheless, results with images from Figures 3 and 4, not shown here because of space constraints, suggest that there cannot be an automatic application of these filters to all types of images.
Fig. 18. Result of the application of algorithm for Shannon’s entropy for the image in Fig. 2, with normalized values for each colour channel.

Fig. 19. Result of the application of algorithm for Shannon’s entropy for the image in Fig. 2, with normalized values for each colour channel.

4 Conclusion

This paper describes the initial research done in the effort to detect natural and artificial zones in images, addressing a problem that was never addressed before. The rationale to use Shannon’s Entropy as the mathematical tool to conclude on the nature of a particular zone was that artificial zones have less variability in colour than natural zones, and therefore, should return a lower value for the entropy.

Initial research results that this may be a line worth pursuing, as some results show promising signs. Nevertheless, there is still a long research path to follow, as many research variables were not sufficiently addressed, for example, the definition of the image and the resolution of the used camera, the types of images to be tested, and also, the controlled conditions on lighting and context. The set of three images used were selected not because they were easy to process, but on the contrary, because they were hard, and yet, some results were promising enough to allow us to continue this research.

Currently ongoing research addresses not only the control of the research variables described before, but also will be extended to include a wider set of images with similar characteristics, including urban and natural outdoor environments, indoor environments with fair conditions of lighting, and finally, indoor thermography images.

Considering the possible adoption of the algorithm based on Shannon’s entropy concept for image analysis in AAL, and the strict requirements on privacy preservation, that can be solved by resorting, for example, to the use of depth information [6], a further development of this research will investigate the applicability of the algorithm to depth images captured by depth sensors, like the Microsoft Kinect® one. The possibility of automatically distinguish natural and artificial areas in the depth frames could enable a significant performance improvement of the currently applied processing algorithms, thanks to the possibility of limiting the amount of depth information to be analysed.
On the subject of image analysis and on the subject of entropy calculation as a analysis tool, the interested reader may wish to read the following research [7-11].

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