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Use of power law models in detecting region of interest

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Abstract

In this paper, we shall address the issue of semantic extraction of different regions of interest. The proposed approach is based on statistical methods and models inspired from linguistic analysis. Here, the models used are Zipf law and inverse Zipf law. They are used to model the frequency of appearance of the patterns contained in images as power law distributions. The use of these models allows to characterize the structural complexity of image textures. This complexity measure indicates a perceptually salient region in the image. The image is first partitioned into sub-images that are to be compared in some sense. Zipf or inverse Zipf law are applied to these sub-images and they are classified according to the characteristics of the power law models involved. The classification method consists in representing the characteristics of the Zipf and inverse Zipf model of each sub-image by a point in a representation space in which a clustering process is performed. Our method allows detection of regions of interest which are consistent with human perception, inverse Zipf law is particularly significant. This method has good performances compared to more classical detection methods. Alternatively, a neural network can be used for the classification phase.

Keywords: Region of interest; Zipf law; Inverse Zipf law; Image encoding

1. Introduction

Automatic detection of regions of interest in images is one of the most critical problems in computer vision. For a human observer, detecting a perceptually important region in an image is a natural task which is done instantaneously, but for a machine it is far more difficult, as the machine lacks the cultural references and knowledge to identify the content of the scene. One of the causes for this difficulty is the subjective nature of the notion of region of interest (ROI). In the most general sense, a ROI, as its name suggests, is a part of the image for which the observer of the image shows interest. Of course, the interest shown by the observer in viewing the image is determined not only by the image itself, but also by the observer's own sensitivity. For a given image, different people could find different regions of interest. However, it can be said, in most cases, regions of interest generally have visually and structurally distinctive features than the rest of the image. Then some structural characteristics can be used to detect the ROI of an image without making hypotheses about the semantic content of the picture. The detection of the ROI consists in finding a region of the image which appears different from the background with respect to low-level features such as contrast, colour, region size and shape, distribution of contours or texture pattern. Different methods have been proposed to detect regions of interest in an image. Some are based on models of low-level human vision, such as the method proposed by Osberger and Maeder [1] which detects perceptually important regions on the image by building importance maps based on various visual characteristics. The method proposed by Itti et al. [2] is based on multiscale centre-surround contrast and the method presented by Syeda-Mahmood [3] uses a segmentation in homogenous colour regions. Other methods are based on different structural characteristics of the image without explicit reference to the human vision. The method proposed by Di Gesu et al. [4] uses symmetry transforms, Stentiford [5] uses dissimilarities in local neighbourhoods, Kadir and Brady [6] use a local measure of entropy to detect salient features in an image, Wang et al. [7] use a wavelet transform and Carlotto and Stein [8] use a fractal model.

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In this paper, we shall use a new approach based on a statistical model which originates in linguistic analysis: Zipf law. This model proved efficient to represent the distribution of the frequencies of words in the form of a power law. It has been discovered in 1949 by Zipf [9] in written English texts, and Zipf distributions have been found in every natural language. Similar power laws have been put into evidence in different domains of human and natural sciences, such as income distribution by Pareto [10] and Gibrat [11], population of cities by Zipf [12] and Gabaix [13], distribution of biological species by Yule [14], distribution of galactic voids by Gaite and Manrubia [15], Internet traffic by Breslau et al. [16] and Huberman et al. [17] and in the structure of music by Manaris et al. [18] and of natural noises by Dellandrea et al. [19]. In the domain of digital images, Zipf law has been used by Vincent et al. [20] to evaluate the distortion of compressed images and by Caron et al. [21] to detect artificial objects in natural environments. The method described in this paper aims to detect the regions of interest in various digital images. A potential application is automatic determination of the ROI for JPEG2000 compression. Some restrictive constrains have been assumed so that a process is possible. We assume the ROI to be detected is a single connected region in the image. The ROI must both have a significant size and appear different from the background with respect to its structural complexity. Most often, the ROI is belonging to the foreground of the scene and contains more details than the background but our method also handles the case when the ROI is more uniform than the background.

The power law model will first be recalled, and then we will present the adaptation that is needed to apply it to image analysis. Then, the detection methods based on Zipf and inverse Zipf laws will be presented, and the influence of initial image segmentation will be discussed.

2. Power law models

The power law distribution model known as Zipf law or rank-frequency law has been determined empirically by Zipf. According to Zipf law, in a topologically ordered set of symbols like a text, the frequency of occurrence of the different symbol patterns, for example the words of the text, follows a power law. To be more precise, different patterns occur in the signal, they are n-tuples of symbols. Let us note as $P_1, P_2, \ldots, P_R$ these patterns. The frequencies of those patterns depend on the signal, let us note them as $N_1, N_2, \ldots, N_R$. Then the patterns can be sorted according to the decreasing order of their appearance frequency. That is to say $N_{\sigma(i)}$ is frequency of pattern $P_{\sigma(i)}$ of rank i.The frequency of appearance $N_{\sigma(i)}$ of the pattern P of rank i is given by

$$N_{\sigma(i)} = ki^{-\alpha}. \tag{1}$$

In this formula, k and α are constants. k is linked to the total length of the observed signal and the value of the exponent α, in the case of English texts studied by Zipf is close to 1. Similar results have been found in texts written in all natural languages, as well as randomly generated texts. This power law model is usually represented graphically in a bi-logarithmic scale diagram, where the logarithm of the frequency of each n-tuple is plotted with respect to the logarithm of its rank. Such a graphical representation is called Zipf plot. This transform allows to introduce a linear relation that can be estimated in an easy way. The least-square regression of the plot can be used to approximate the power law exponent.

Different interpretations have been proposed to explain the existence of power law distributions. Zipf's own explanation was based on the principle of least effort: a power law distribution of the word frequencies tends to minimize the effort of both the speaker and the listener in communication. However, not all the phenomena where power law distributions are observed, can be explained in that way. Therefore, other interpretations have been proposed by Mandelbrot [22], Simon [23] and more recently by Reed [24], where the existence of power laws is explained by the properties of lexicographical trees, Brownian motion and stochastic birth and death processes.

Another power law model has been discovered by Zipf [25] in his work on natural texts. It is the so-called inverse Zipf law. According to this law, the number I of distinct words which have the frequency f is given by

$$I(f) = af^{-b}. \tag{2}$$

In this formula, a and b are constants and the value of exponent b is generally close to 2 in the case of natural texts. In fact, this formula is verified only for the least frequent words.

As for Zipf law, inverse Zipf law can be represented in a bi-logarithmic scale diagram. Such a representation is called inverse Zipf plot. Inverse Zipf law has been used by Cohen et al. [26] and Ferrer and Solé [27] to study the properties of natural and random texts. Inverse Zipf law expresses the diversity of the lexical spectrum of a text and it can be used to discriminate between natural texts and artificially generated texts, as the values of the parameters of the power law model are different for the two types of texts.

Since power law models can discriminate between natural and artificial texts, it might be possible to adapt those models to image analysis and use them to detect some specific features in an image, and therefore to detect a ROI.

3. Application to images

Some years ago, Lindsey and Strömberg [28] used the frequencies of simple features. In this study, the approach finds its base in some law that has been verified in different fields. We show both Zipf law and inverse Zipf law can be used for image analysis. To adapt the model to image analysis, it is necessary to define the equivalent of the notion of word in the case of images. In order to respect the usual topology that structure the plane of the image, we will use image patterns defined as blocks of 3×3 adjacent pixels, such as words are defined as strings of adjacent letters. The two main differences between words and image patterns is that the image is bi-dimensional, unlike the text, and in our case the patterns will have a fixed size, unlike the words which have a variable length. In usual images where each pixel is coded on a byte, the grey levels of the image cannot be used directly. Indeed, the number of possible different patterns would be too large for the statistical repartition of the frequencies to be significant. It is therefore necessary to define a pattern coding which reduces the number of distinct patterns. It will eliminate also the influence of the small variations of intensity. A simple way to achieve this is to quantize the grey level that is to divide the grey scale into a small number of classes and to assign at each pixel the value of the class. The class value $c(x, y)$ of the pixel $g(x, y)$ is given by the formula (3) where N is the number of classes:

$$c(x, y) = \mathrm{int}\left[\frac{Ng(x, y)}{255}\right]. \tag{3}$$

The number of classes must be chosen to minimize both the number of distinct patterns and the distortion of the image, the loss of information due to the coding process. The best results have been obtained with nine classes, it is the lowest number of classes which can be used without visible distortion of the image. An example of pattern obtained with this method is shown in Fig. 1.

In order to verify that either Zipf law or inverse Zipf law hold on an image, the image is scanned with a 3×3 mask, the patterns are encoded and the occurrence frequency for each different pattern is computed. The patterns are coded according to the pixels grey level in the considered window. In the case of Zipf law, the patterns are sorted in the decreasing order of their appearance frequency, and the frequency for each pattern is plotted with respect to its rank in a double-logarithmic scale diagram. In fact, only the frequencies of the patterns which appear at least twice in the picture are represented on the plot. Such a graphical representation is called Zipf plot. In the case of inverse Zipf law, the number of distinct patterns having a given frequency is counted, and the results are also represented in a double-logarithmic scale diagram, known as inverse Zipf plot.

255	210	210
25	2	34
40	2	40

8	7	7
0	0	1
1	0	1

Fig. 1. Original pattern (left) and pattern coded with nine-class method (right).

An example of Zipf and inverse Zipf plots associated with a photographic image is shown in Fig. 2. We can notice inverse Zipf law is a very good model for the image. Besides, as far as Zipf law is concerned, the quality of the model is not so good. A close look at the graph shows two linear zones. Two power laws models reveal different characteristics of the image. With Zipf law, the graphical representation can be divided into two parts, corresponding to different patterns types. The most frequent patterns represented by the left part of the plot correspond to the most frequent patterns. They are present in the homogenous zones of the image. The right part of the plot corresponds to smaller details and contours. The two parts of the curve, taken separately are linear, so the distribution of the image pattern frequency is modelled by two independent power laws, one for homogenous regions and the other for small regions. Two different structures are highlighted. In the case of the inverse Zipf law, the plot is linear for the least frequent patterns and means the distribution of the number of distinct patterns, with respect to their frequencies, follows a power law. Therefore, inverse Zipf law holds in the case of grey level images encoded through 3×3 windows in the neighbourhood of each pixel.

We are now to analyse the differences of the characteristics of Zipf and inverse Zipf plots according to the structural content of the image. Fig. 3 shows two different zones of the same image and the associated Zipf plots. In the case of a uniform background zone, there is high number of homogenous patterns, so the slope of the left part of the plot is higher, and the right part of the plot appears comparatively flat. On the contrary, in regions containing more details, the plot is more linear and with a larger slope.

The inverse Zipf plots of both types of zones also show noticeable differences. In image zones containing many details such as foreground objects, the number of patterns which have a low frequency of appearance is considerably higher, and therefore the inverse Zipf plot has a higher slope than in the case of more uniform regions.

The characteristics of Zipf and inverse Zipf plots are different according to the amount of detail in the image. Since the regions of interests generally contain more details than the background of images, Zipf and inverse Zipf laws can be used to detect regions of interest in images (Figs. 3 and 4).

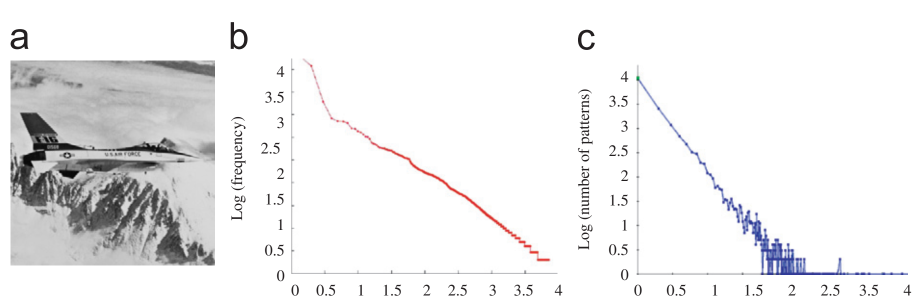

Fig. 2. Inverse Zipf plot (b) and inverse Zipf plot (c) associated with the image (a).

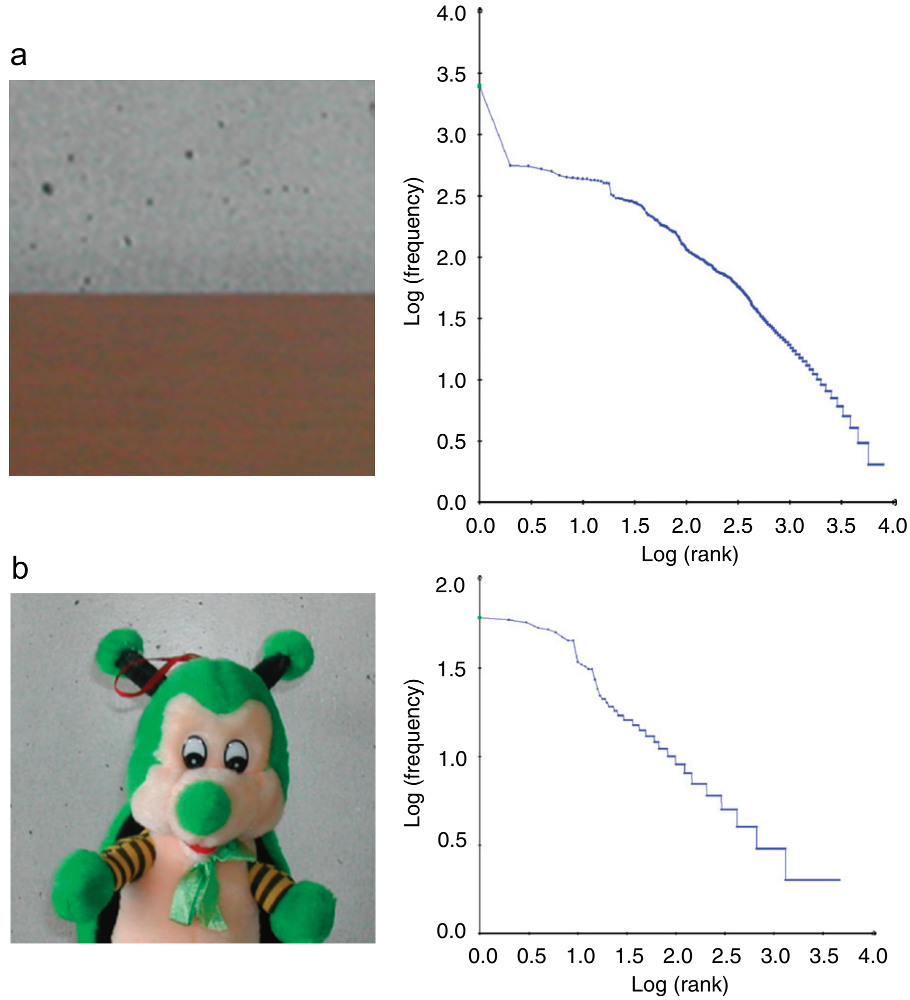

Fig. 3. Zipf plots of a uniform region (a) and of a region containing many details (b).

4. Detection using Zipf law

The ROI of the image can be defined as a part of the image whose structural content differs from the background of the picture. Power law models can provide an indication on the structural content of the picture, however, they provide no spatial information by themselves. Therefore, we are introducing a more local study followed by a global analysis of the local results. In order to reveal some local information, it is necessary to divide the image into sub-images as shown in Fig. 5. In each of the sub-images, Zipf or inverse Zipf law parameters can be estimated. Then the sub-images are classified according to the characteristics of the corresponding Zipf plot. The classification method consists in representing the sub-images in a multidimensional space of characteristics. Then the set of points is clustered in two classes in order to detect the ROI.

In the case of Zipf law, the characteristics to be used are the slopes of the two parts of the plot. The two zones are determined on the graph by point P being the most distant point from the line connecting the two extreme points of the plot as shown in Fig. 6.

For example, the horizontal coordinate x of each point of the cluster represents the slope of the left part of the corresponding Zipf plot and the vertical coordinate y represents the slope of the right part of the plot. The slopes are computed using least-square regression method on a re-scaled representation to give equal weight to each point.

It has been determined experimentally that in most images, the sub-images containing more detailed objects have Zipf plots where the slope of the right part is slightly lower than the slope of the left part. They are represented on the graph by points for which $y < x$ and $x < G_x/1.2$ hold, with G_x the horizontal coordinate of the centre of gravity of the cluster. Nevertheless, not every sub-image satisfying these conditions is part of the main ROI. Therefore, the largest connected component of those sub-images is the only one to be considered as “the” ROI. This region may contain holes. They can be filled by including the sub-images which have all their neighbouring sub-images belonging to the ROI. An example of detection using this method is shown in Fig. 7.

5. Detection using inverse Zipf law

Like Zipf law, inverse Zipf law can be used to detect regions of interest in an image. The image is again partitioned into sub-images and the characteristics of the inverse Zipf plots

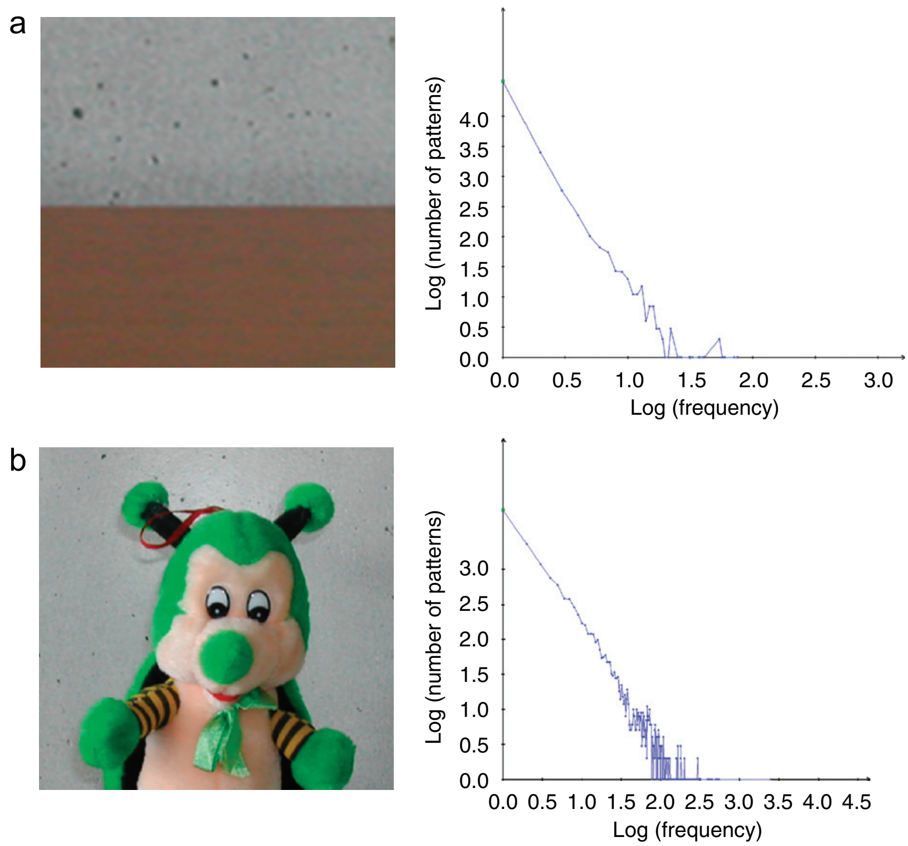

Fig. 4. Zipf plots of a uniform region (a) and of a region containing many details (b).

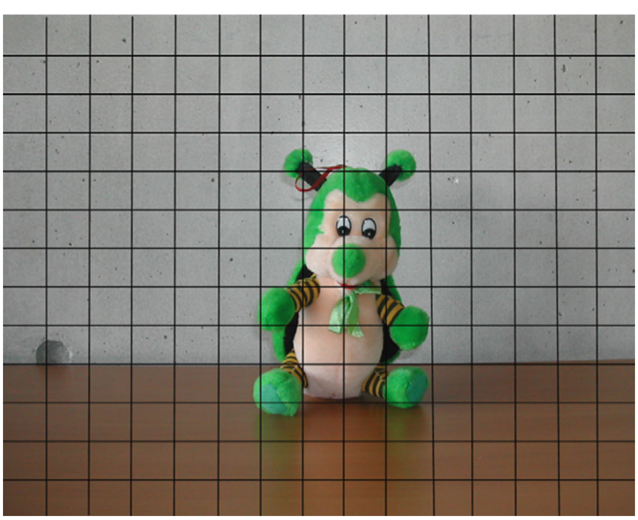

Fig. 5. Segmentation of the image in sub-images.

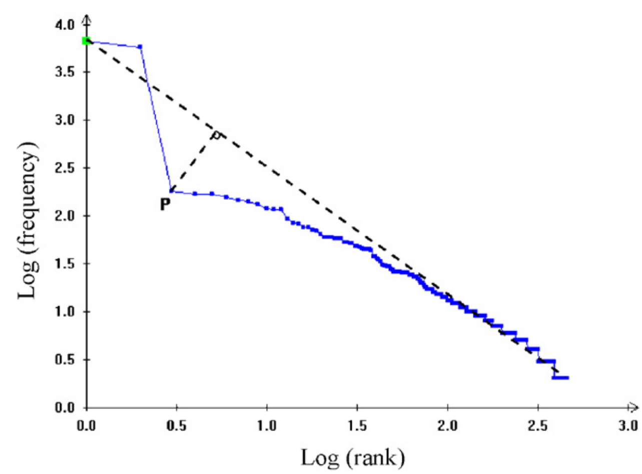

Fig. 6. Separation between the two parts of Zipf plot.

corresponding to the sub-image are represented graphically by points in a graph. The significant characteristics of an inverse Zipf plot we are using are its slope and the number of patterns which appear only once in the picture. On the graphical representation, the horizontal coordinate represents the slope and the vertical coordinate represents the number of unique patterns. The set of points associated with sub-images is clustered into two classes, respectively, the ROI and the background, according to the values of the slope of the distribution and the number of unique patterns. In most images, the ROI contains more details than the background, so it will be represented by the part of the sub-images corresponding to the highest values of the slope and/or of the number of unique patterns. The separation between the two classes can be defined by the centre of gravity of the set. If we use the number of unique patterns as a detection criterion, the ROI is defined as the

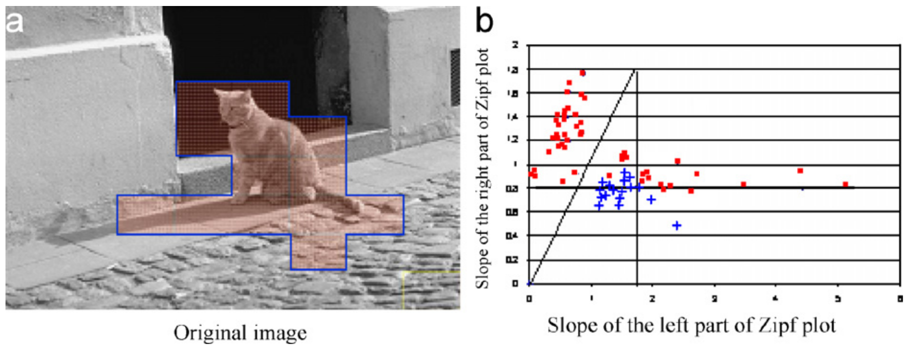

Fig. 7. In (a) region of interest extracted using Zipf law, in (b) the sub-images are figured in the representation space with the clustering in two classes ROI and background.

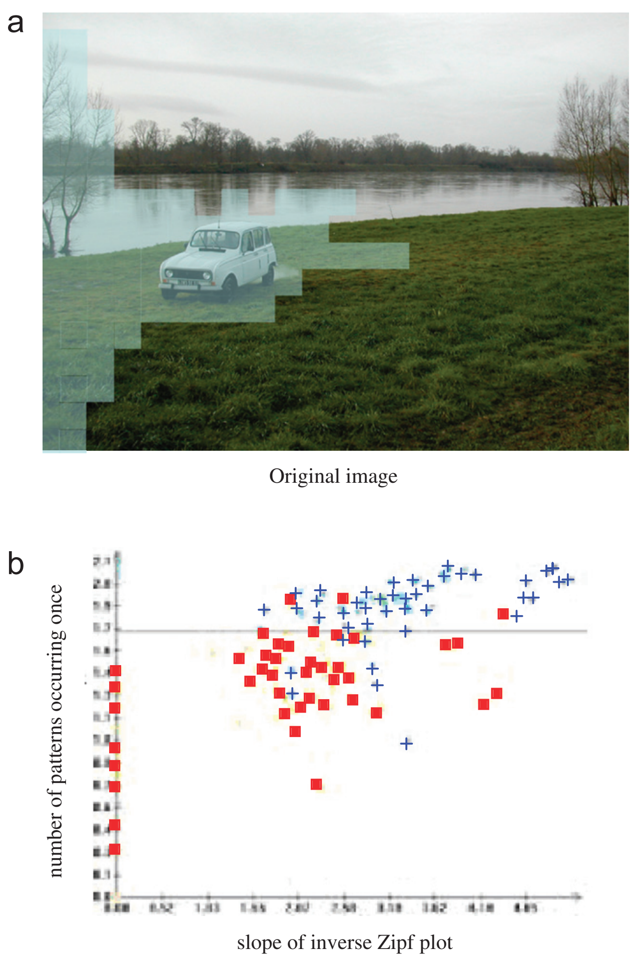

Fig. 8. Region of interest detection indicated in (a) using inverse Zipf law. The representation of the sub-images is figured in (b) where the clustering is shown.

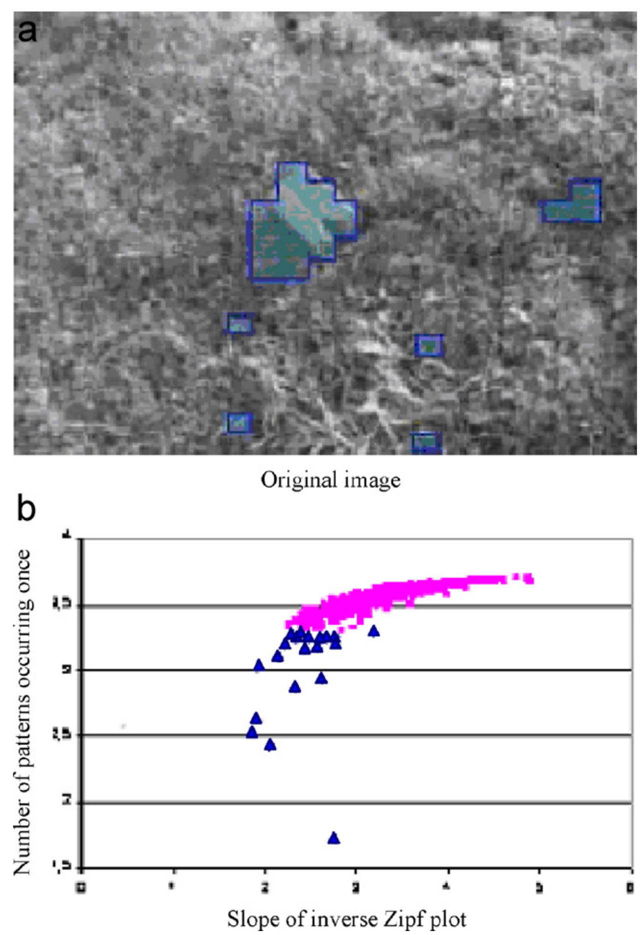

Fig. 9. Detection of an object more uniform than the background in (a) the representation of the sub-images is figured in (b) where the clustering is shown.

largest connected component of the sub-images represented by points situated above the centre of gravity of the cluster. If the ROI contains holes, as with Zipf law, they can be filled by including the sub-images with all neighbours already belonging to the region. The discrimination between the two classes can be adjusted dynamically in order to maintain the surface of the ROI between 20% and 50% of the total area of the image. An example of ROI detected using this method is shown in Fig. 8. The blue area in this case seems too large.

Unlike in the previous case, the ROI consists of a more uniform object on a textured background. It is still possible to detect the ROI using the same method and detecting the case in an automatic way. This case occurs if more than 50% of the patterns of the whole image appear only once in the picture. The ROI is associated with the lower part of the graph. An example of such a ROI detected in such a way is shown in Fig. 9.

It is also possible to use the slope of the inverse Zipf plots instead of the number of unique patterns as a detection criterion. In this case, the ROI is represented by the points situated at the right of the gravity centre of the set, or at the left in the case of uniform object in textured backgrounds. The results are similar to those obtained with the previous criterion. In both cases, the regions of interest detected with this method tend to be larger than those which would be considered as such by human observers and often includes parts of the background. An improvement can be made by using the two characteristics of the inverse Zipf plot to determine the ROI. In this case, the ROI is the largest connected component of the sub-images represented by the points in upper right part of the cluster. This method allows the detection of more precise ROI as shown in Fig. 10.

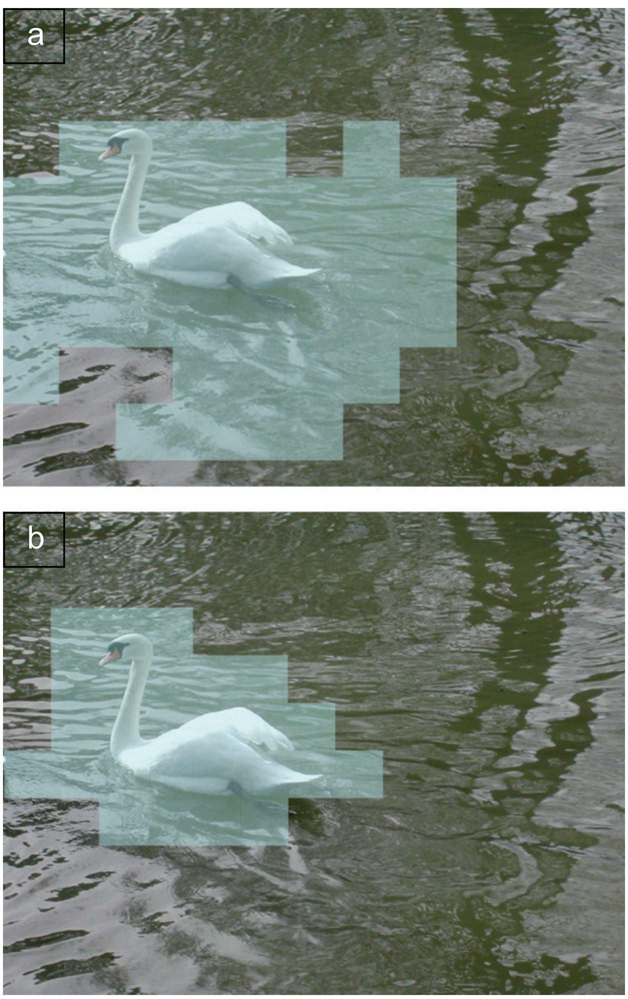

Fig. 10. Region of interest detected based on the number of unique patterns (a) and on the two characteristics (b).

6. Influence of initial segmentation

The size of the ROI depends on the size of the whole image. Here we are going to study the influence of the image size on the characteristics of its pattern distribution. Indeed, the size of the sub-images must be chosen properly. They must be large enough to present a statistically significant pattern distribution but also be small enough to allow a precise determination of the ROI. As an image always aims to show something, and to bring some information to the observer, we have chosen to consider sub-images with no absolute dimension but relative dimension, related to the initial dimension of the image. The whole image is divided in a certain number of sub-images. To determine the best size of the image, a series of tests was conducted with the same images segmented into different numbers of sub-images. An example of test result is shown in Fig. 11. The image has been segmented in 64 $(=8 \times 8)$, $361 = (19 \times 19)$ and $1024 = (32 \times 32)$ sub-images, and the inverse Zipf detection method has been applied. When segmented in 8×8 sub-images, the object is not detected because the image is misclassified as having an object of interest which is more uniform than the background. With segmentation in 361 sub-images the ROI is correctly detected, and with the segmentation in 1024 sub-images, some uniform parts of the object are not detected as parts of the background and textured background regions are classified as regions of interest. In most digital photographic images, the best detection results are obtained when the surface of each sub-frame is about 5000 pixels, which correspond in the case of the image presented in Fig. 11 to a segmentation in 19×19 sub-images of the initial image. Indeed, the number of pixel must be large enough as we consider a statistical approach.

7. Experimental results

The method has been tested on a base of 100 digital photographic images containing a distinct ROI which has been determined by a human observer. The images have been gathered

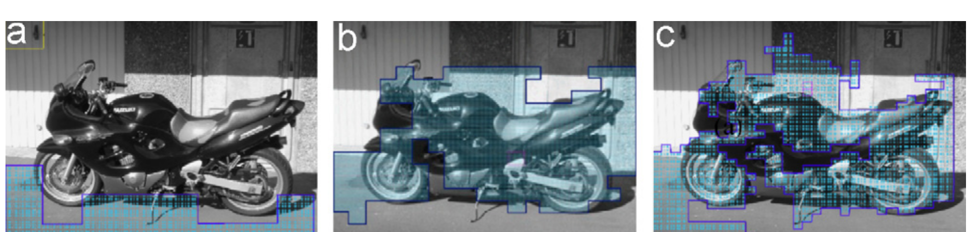

Fig. 11. Regions of interest detected using inverse Zipf law with an initial segmentation in 8×8, 19×19 and 32×32 sub-images.

Table 1
Detection results with different methods

Method	Detection rate (%)
Zipf law	56
Inverse Zipf law	
Number of unique patterns	80
Slope of the distribution	78
Both parameters	84

among different public image databases. The images are uncompressed or mildly compressed and their size varies from 256×256 to 2000×1500. The images have been segmented into the optimal number of sub-images according to their size. The detection is considered to be successful if the subjective ROI is included in the region detected by the process. The results of the different methods are detailed in Table 1 below.

We may observe that the use of inverse Zipf law gives considerably better performances than Zipf law for detecting the ROI in images. However, the ROI detected with inverse Zipf law is often larger than the true ROI of the picture. Our method has been compared with two other detection methods, a fractal method adapted from those developed by Carlotto and Stein [8] and the method of importance maps proposed by Osberger and Maeder [1]. The fractal method consists in partitioning the image in blocks of size 32×32 and computing the fractal dimension D of the grey level elevation surface of each block using a box-counting approach. The ROI consists in the largest connected component of blocks which satisfy

$$D < \bar{D} - \sigma_D \quad \text{or} \quad D > \bar{D} + \sigma_D,$$

where $\bar{D}$ is the average value and σ_D is the standard deviation of the fractal dimension on all the image blocks. The ROI has been detected in only 58% of the test images.

The method of importance maps consists in segmenting the image into regions using a split-and-merge segmentation algorithm and in computing for each region perceptual importance factors based on contrast, size, shape and position of the region with respect to the centre and the border of the picture. The importance value of each region is the squared sum of the five importance factors, normalized in the [0..1] interval, the most important region having an importance value of 1. This method allows the detection of the ROI in 83% of the test images. However, this method often allows to detect a part of the subjective ROI, particularly when several regions are involved.

8. Conclusion

Power law models such as Zipf and inverse Zipf laws can be used to characterize the structural complexity of an image. Our former nonconstrainable hypotheses show that the use of a method based on those models allows to detect automatically the ROI of an image, given that this ROI appears sufficiently distinct from the background. Both Zipf law and inverse Zipf law can be used to detect ROI, however, the method based on inverse Zipf law produces better results for our application. The method allows the detection of ROI not only when the object to be detected is more detailed than the background, but also when it appears more uniform and our method is able to adapt to both cases. Our detection method based on inverse Zipf law has better performances than box-counting fractal methods and equivalent with importance map perceptual method. A neural network can be used for the classification, however, this method is not very adapted to our application due to the disparity of the images, a no-explicit reference classification method gives better results in our case. A possible improvement of the method would be to operate a fusion of all the parameters we have extracted or the fusion of the characteristics of power law models with the measures of more classical perceptual features of the image such as edge detection or contrast measures. Indeed, our goal was to show the interest of applying Zipf law model rather than proposing a final process for ROI detection. Other applications of power law models in images can be found, such as image indexation and content-based image retrieval, as well as the segmentation of video sequences.

References

[1] W. Osberger, A.J. Maeder, Automatic identification of perceptually important regions in an image, in: 11th International Conference on Pattern Recognition, vol. 1, 1998, pp. 701–704.
[2] L. Itti, C. Koch, E. Niebur, A model of saliency-based visual attention for rapid scene analysis, IEEE Trans. Pattern Anal. Mach. Intell. 20 (11) (1998) 1254–1259.
[3] T.F. Syeda-Mahmood, Data and model-driven selection using colour regions, Int. J. Comput. Vision 21 (1) (1997) 9–36.
[4] V. Di Gesu, C. Valenti, L. Strinati, Local operators to detect regions of interest, Pattern Recognition Lett. 18 (1997) 1077–1081.
[5] F. Stentiford, An estimator for visual attention through competitive novelty with application to image compression, in: Picture Coding Symposium, Seoul, Korea, April 2001, pp. 25–27.
[6] T. Kadir, M. Brady, Saliency, scale and image description, Int. J. Comput. Vision 45 (2) (2001).
[7] J.Z. Wang, J. Li, R.M. Gray, G. Wiederhold, Unsupervised multiresolution segmentation for images with low depth of field, IEEE Trans. Pattern Anal. Mach. Intell. 23 (1) (2001) 85–90.
[8] M.J. Carlotto, M.C. Stein, A method for searching artificial objects on planetary surfaces, J. Br. Interplanet. Soc. 43 (1990).
[9] G.K. Zipf, Human Behavior and the Principle of Least Effort, Addison-Wesley, Reading, MA, 1949.
[10] V. Pareto, Cours d'économie politique, Rouge, Lausanne, 1897.
[11] R. Gibrat, Les Inégalites Économiques, Librairie du Recueil, Paris, 1931.
[12] B.M. Hill, Zipf's law and prior distributions for the composition of a population, J. Am. Statist. Assoc. 65 (1970) 1220–1232.
[13] X. Gabaix, Zipf's law for cities: an explanation, Q. J. Econ. 114 (1999) 739–767.
[14] G.U. Yule, A mathematical theory of evolution based on the conclusions of Dr. J.C. Willis, F.R.S., Philos. Trans. Royal Soc. London (Ser. B) 213 (1925) 21–87.
[15] J. Gaite, S. Manrubia, Scaling of void sizes and fractality in the galaxy distribution, Mon. Not. Royal Astron. Soc. 335 (4) (2002) 977–983.
[16] L. Breslau, P. Cao, L. Fan, G. Phillips, S. Shenker, Web caching and Zipf-like distributions: evidence and implications, in: Proceedings of INFOCOM'99, IEEE Press, New York, 1999.
[17] B.A. Huberman, P. Pirolli, J. Pitkow, R. Lukose, Strong regularities in world wide web surfing, Science 280 (1998) 95–97.
[18] B. Manaris, C. McCormick, T. Purewal, Searching for beauty in music, Applications of Zipf's law in MIDI-encoded music, Science, the arts and

the humanities: connections and collisions, in: 2001 Sigma Xi Forum, Raleigh, NC, November 8–9, 2001.
[19] E. Dellandrea, P. Makris, N. Vincent, Zipf analysis of audio signals, Revue Fractals, World Scientific, Singapore, vol. 12(1), 2004, pp. 73–85.
[20] N. Vincent, P. Makris, J. Brodier, Compressed image quality and Zipf's law, in: Proceedings of International Conference on Signal Processing (ICSP-IFIC-IAPRWCC2000), Beijing, China, 2000, pp. 1077–1084.
[21] Y. Caron, P. Makris, N. Vincent, A method for detecting artificial objects in natural environments, in: International Conference on Pattern Recognition (ICPR2002-IAPR), Quebec, Canada, 2002, pp. 600–603.
[22] B.B. Mandelbrot, An informational theory of the statistical structure of languages, in: W. Jackson (Ed.), Communication Theory, Betterworth, 1953, pp. 486–502.
[23] H.A. Simon, On a class of skew distribution functions, Biometrika 42 (1955) 425–440.
[24] W. J Reed, The Pareto, Zipf and other power laws, Econ. Lett. 74 (2001) 15–19.
[25] G.K. Zipf, Psycho-Biology of Languages, Houghton-Mifflin, Boston, MA, 1935.
[26] A. Cohen, R.N. Mantegna, S. Havlin, Numerical analysis of word frequencies in artificial and natural language texts, Fractals 5 (1) (1997) 95–104.
[27] R. Ferrer i Cancho, R.V. Solé, Zipf's law and random texts, Adv. Complex Syst. 5 (1) (2002) 1–6.
[28] C.S. Lindsey, M. Strömberg, Image classification using the frequencies of simple features, Pattern Recognition Lett. 21 (2000) 265–268.

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