Deterministic Tourist Walks as an Image Analysis Methodology Based

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Abstract. Textures are important visual attribute used in image analysis. This paper presents a novel methodology, based on a deterministic walk, to texture analysis and texture characterization. Most of the methods adopted to classify textures deal with a defined fixed scale of texture. The method proposed here explores the set in all scales and is able to characterize efficiently different texture classes. The paper presents the deterministic walk technique and its results for two experiments using Brodatz images.

1 Introduction

Image Analysis is a field of computer vision and artificial intelligence responsible for the extraction of meaningful information from images. Among several attributes, texture is an important visual attribute used in image analysis. Texture analysis has a broad range of applications, such as: aid of diagnoses in medical images [1], remote sensing [2], analysis of geological images [3] and microscope images [4].

Although there is not a formal specification of the texture analysis, this attribute is directly related to the distribution of pixels in a certain region of the image. It represents an important source of information. Generally, textures can be classified as micro and macro textures according to the size of the set of pixels analyzed. By micro textures we mean the analysis of a small parts of the image, while for macro texture the analysis of the whole image. Most of the techniques used in image retrieval are devoted to the micro textures analysis [5,6]. The number of methods applied to macro textures is still restricted, due to the inherent difficulty in the analysis [7].

Recently we have proposed a new method for texture characterization based on a deterministic dynamics. Consider walkers leaving each pixel of an image.

Each walker does not interact with the others. For a given time step, each walker has information about the eight next nearest neighbor pixels and moves towards the direction of minimum intensity difference among the ones that have not been visited in the previous μ time steps. For $\mu = 0$, no dynamics is allowed. For $\mu = 1$, the walker always goes to the minimum intensity difference direction, so that after a time transient, the trajectories end on cycles of period two. This cycle consists of two pixels having mutually the minimum intensity differences between themselves. More interesting cycle distributions occur for $\mu \geq 2$. In this case each trajectory, after a transient time, ends in a cycle with period $p \geq \mu = 1$. In particular, cycles with period p much greater than the memory μ are allowed. It is the range of cycle periods which allows the image analysis from the local scale of μ pixel up to a large scale of size of the number of pixels N .

Our main interest is to obtain an image signature from the time transient and cycle period joint distribution. A naive approach to this analysis has been described in Ref. [8], where we have shown the potential use of these joint distributions for texture analysis in images. A more sophisticated analysis, using the non-parametric Flexible Discriminant Analysis (FDA) on the joint distribution furnished a more reliable classification [9].

Our presentation is divided as follows. A brief review of the considered deterministic walk in Section 2. In Section 3, we modify these walks to apply them to image analysis. In Section 4, from the transient time and cycle period obtained from the walker trajectory we build texture signature vectors. Also we set up experiment sets to compare the performance of two of the proposed texture signature vectors to 400 images of 40 different Brodatz's texture classes. In Section 5, we show the superior performance when multiple μ values are used. Finally in Section 6, the conclusions and improvement of the methods are discussed.

2 Deterministic Tourist Walk

Although not as thoroughly studied as random walks [10,11], the study of deterministic walks has attained the interest of researchers [12,13,14,15]. Here, we are interested in exploring a partially self-avoiding deterministic walk algorithm, known as the tourist walk (TW) [16,17,18,19,20,21] for image analysis purposes.

The tourist walk algorithm can be pictorially viewed as a tourist wishing to visit N cities randomly distributed in a map of d dimensions. The tourist starts his route in a given city of this map and moves according to the following deterministic rule: *go to the nearest city, which has not been visited in the last μ time steps*. For $\mu \geq 1$, self-avoidance is limited to the memory window $\tau = \mu - 1$, which represents a characteristic time to the city to become attractive to the tourist again (refractory time). The trajectories can intersect outside this memory range. Each tourist trajectory consists of a transient part of length t (new cities are visited) and a final cycle of period p (no new cities are visited any longer). The trajectory is complex and depends strictly on the starting point and on the configuration of the data set. The only known relation that holds is $p \geq \mu + 1$. The tourist movements are entirely performed based on the neighborhood rank. These ranks are conveniently represented by a neighborhood table, which

neglects the distances among the cities. This feature leads to invariance in scale transformations [21].

We call the attention to several aspects of these deterministic walks:

1. At each time interval the tourist moves from one city to another, regardless the distance between them.
2. Starting from different cities in the map, the tourist performs different trajectories with variable transient times (which can even be null $t = 0$) and end in cycles with period $p \geq \mu + 1$.
3. The trajectories are different for different initial conditions, but several trajectories can end in the same cycle with a given period p .

Although easy to formulate and not too complicated to implement numerically, this algorithm may present a complex behavior according to the chosen memory window μ . This intriguing behavior can be captured with the transient time and period joint distribution $S_{d,\mu}^{(N)}(t, p)$. Here we show that the joint distributions $S_{d,\mu}^{(N)}(t, p)$ can be efficiently used as features for image analysis. In the following we show some examples of known analytical joint distributions for Poissonic landscape.

The deterministic tourist walk with memory $\mu = 0$ is trivial since the walker does not move at each time step. The joint distribution is simply given by: $S_{d,0}^{(N)}(t, p) = \delta_{t,0} \delta_{p,1}$, where $\delta_{i,j}$ is the Kronecker's delta.

With memory $\mu = 1$, the walker must leave the visited city at each time step. The transient and period joint distribution is obtained for $N \gg 1$ [22]: $S_{d,1}^{(\infty)}(t, p) = \Gamma(1 + I_d^{-1})(t + I_d^{-1}) \delta_{p,2} / \Gamma(t + p + I_d^{-1})$, where $t = 0, 1, 2, \dots$, $\Gamma(z)$ is the gamma function and $I_d = I_{1/4}[1/2, (d+1)/2]$ is the normalized incomplete beta function. We stress that this transient time distribution has been calculated for Poissonic process. It does not lead to exploration of the random medium since after a short transient time, the tourist gets trapped in pairs of cities that are mutually nearest neighbors.

Interesting phenomena occur when greater memory values are considered. In this case, the cycle distribution is no longer peaked at $p_{min} = \mu + 1$, but presents a whole spectrum of cycles with period $p \geq p_{min}$, with possible power-law decay [16,17,18]. Determinism imposes serious restrictions as it can be seen in $\mu = 2$ one-dimensional systems, where all odd periods above $p_{min} = 3$ are forbidden, as well as the even period $p = 6$.

3 Modified Tourist Walk

In the context of images ($d = 2$), one can consider each pixel as a point (or city). In the original algorithm the neighborhood table has size of the order N^2 , where each point is ranked with respect to the remaining $N - 1$ other points. Notice that μ ranges from zero to $N - 1$, where all cities are visited (full self-avoiding circuit).

For images, the algorithm has been modified since each pixel interacts only with its first and second neighbors and the walker goes always to the direction

of minimum intensity difference (gradient). Thus the neighborhood table has a maximum size of $N \times 8$. For open boundary condition, the surface and corner pixels have five and three next and second next nearest neighbors, respectively.

Starting from each pixel, the walker moves according to the deterministic rule of going to the pixel with nearest intensity compared to the present pixel intensity, so that the given intensity difference has not been attained in the preceeding μ steps. From these walks, the transient time and cycle period of the trajectories are calculated and the joint distribution is constructed.

The occurrence of ties is resolved by choosing the first pixel in the counter clockwise direction, preserving the deterministic nature of the algorithm. This approach is not invariant to image rotation. For a given image and the same image with 90° -tilt feeded to the algorithm, different joint distributions are produced. This suitable difference for texture characterization is due the deterministic way of resolving intensity difference ties.

Differently from the original problem, the tourist walk is not performed in a non-correlated random media but in a correlated medium, the image. Similarly to the previous studies [8,9], the image analysis consists exploring the joint distribution properties over the image and compose a texture signature curve.

4 Experiments

The tourist walk transient time and cycle period joint distributions have been obtained for different memory values using open boundary conditions to the images from the book of Brodatz [23]. These images form a set largely used in computer vision and image processing literature as benchmark for texture analysis. In the computer experiment, each image has 200×200 pixels with 256 gray levels and 40 classes, with 10 samples each, have been employed. One example of each these 40 classes are depicted in Figure 1. Experiments have been idealized to show the high potential of the method to analyze and characterize texture images.

4.1 Transient Time and Cycle Period Joint Distribution

It is important to stress that the transient time has the role of counting different intensity gradients while the cycle detects a kind of pattern that eventually an image may display. The memory μ has the role of setting the minimum pattern scale.

In Figure 2 three different classes of Brodatz's textures are depicted and for each class, the transient time and cycle period joint distribution of the modified tourist walk is display for three different memory values. Observe the existence of a pattern for the joint distribution for each considered texture class. This stresses the potentiability to discriminate different texture classes from these distributions. Also, it is clear that the large the memory values are, the broader the distribution is. This means that different μ values sample different image characteristics indicating the possibility to have an optimum μ value for better

Fig. 1. One example of each of the 40 Brodatz's classes considered. Each image has 200×200 pixels and 256 grey levels.

image classification. The signature curves obtained from the joint distributions have been used to characterize and classify the images used in the experiment.

Operationally one has a three-dimensional array where one of the axis represents the transient time. The other axis represents the cycle period. When these two axes are combined, they represent the joint distribution $S_{\mu}^{(N)}(t, p)$. The third axis represents the memory, so that slices along the μ axis give $S_{\mu}^{(N)}(t, p)$.

A large amount of information is contained in this three-dimensional array. This implies to difficulties when dealing with pattern recognition. Our main objective is to extract texture information, in a simple form, using signatures.

4.2 Texture Signature Vector

Signatures concentrate the desired texture information to few elements of a vector. For instance, for images of 200×200 pixels, signatures are vectors of a typical size of 25 elements.

The signature curves are feature vectors extracted from the joint distributions and they are used to characterize and classify the images by the texture pattern. In the first approach the feature vector ψ is constructed from the joint distribution of a specific μ value. The parameters t and a indicate the maximum number of transient time and the maximum number of attractors to be considered, respectively:

$$\psi_{\mu}(t, a) = [S_{2,\mu}^{(N)}(0:t, \mu+1) S_{2,\mu}^{(N)}(0:t, \mu+2) \dots S_{2,\mu}^{(N)}(0:t, \mu+a)] . \quad (1)$$

Fig. 2. Three different classes of Brodatz's textures are depicted in panels from (a), (e) and (i). For each class, the transient time and cycle period joint distribution of the modified tourist walk is display for three different memory values: $\mu = 2$ (pannels: (b), (f) and (j)), $\mu = 3$ (pannels: (c), (g) and (k)) and $\mu = 5$ (pannels: (d), (h) and (l)).

To study the influence of the memory on the time transient and cycle period distribution and consequently its influence in the sample classification, the experiments have been performed with $t = 4$ and $a = 5$ so that each signature vector has 25 elements. Experiments have been carried out for $\mu = 2, 3, 5, 7$ and 11.

In the second experiment only the first two time transients ($t = 0$ and $t = 1$) and two cycle periods $a = 2$ are considered for $\mu = 2, 3, 5, 7$ and 11 and the signature vector in this case is the concatenation of the simpler fixed signature vectors

$$\varphi(\mu_i, \mu_f) = [\psi_{\mu_i}(2, 2) \dots \psi_{\mu_f}(2, 2)] . \quad (2)$$

4.3 Flexible Discriminant Analysis

In both experiments, the Brodatz's images have been characterized by modified tourist walk texture signature. A discriminant data analysis technique has been performed, based on these features. The statistical analysis has been carried out with the R 2.1.1 system [24] and the employed technique has been the *flexible discriminant analysis* (FDA) [25]. This is a generalization of *linear discriminant analysis* (LDA). It is more sofisticate analysis than LDA, once it uses

Table 3. Confusion matrix showing the classification results for 40 classes of texture images, for the combining μ method. Classification error = 0.0525.

true obj	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40			
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signature vector. This approach leads to a significant increase of the method classification capacity. The composed signature vector has been generated collecting the five more significant elements from each single μ signature vector leading to 25 elements. The confusion table of this set of experiments is presented in Table 3 and the error is of 0.0525.

Collecting six elements from the single signature vector leading to 30 elements in the composed signature, the error is of 0.0500.

The results of these preliminary experiments with the modified tourist walk transient time and cycle period joint distribution with several memory values combined with a signature vector and a powerfull statistical multivariate analysis show the potential use of them as an efficient image classification method.

The new treatment proposed here diminishes the individual importance for each μ value, but stresses the role of small values either for μ or the transient time and cycle period. This conclusion is corroboreted with the small error taxes for the second experiment

6 Conclusion

We have presented a new method of feature extraction of image textures based on the deterministic tourist walk. The methods most commonly used deals with

defined scales of pixel distributions. The distribution of transient times and periods of a set of data (image) present a wide range, capturing details on the organization of pixels from the micro to the macro scales and the resulting curve is strictly related to the configuration of the data set. We have showed that the joint distribution of the modified TW is an efficient tool for texture classification. We have realized two experiments using the modified TW and discriminant analysis to classify Brodatz textures. The results presented in this paper, show the great potential of the modified TW to be used as a texture analysis methodology.

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