Periodicity and Texel Size Estimation of Visual Texture Using Entropy Cues

Estimación de la Periodicidad y el Tamaño del Texel en Textura Visual Utilizando Indicadores de Entropía

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Abstract. Texture periodicity and texture element (texel) size are important characteristics for texture recognition and discrimination. In this paper, an approach to determine both, texture periodicity and texel size, is proposed. Our method is based on the entropy, a texture measure computed from the Sum and Difference Histograms. The entropy value is sensitive to the parameters in such histograms and takes its lowest value when the parameters match with texel size or its integer multiples, in any specific direction. We show the performance of our method by texture synthesis, tiling a sample of the detected size and measuring the similarity between the original image and the synthesized one, showing good results with regular textures and texels with different shapes, being useful for practical applications as well because of its simple implementation.

Keywords: Image Processing, Texture, Size and Shape, Texture Periodicity, Entropy.

Resumen. La periodicidad de textura y el tamaño del elemento de textura (texel), son características importantes para el reconocimiento de texturas y su discriminación. En este artículo se propone un enfoque para determinar tanto la periodicidad de textura como el tamaño del texel. Nuestro método está basado en una medida de entropía de textura, calculada a partir de los histogramas de sumas y diferencias. El valor de la medida de entropía es sensible a los parámetros de tales histogramas y alcanza un valor bajo cuando dichos parámetros coinciden con el tamaño del texel o sus múltiplos enteros, en una determinada dirección. El rendimiento de nuestro enfoque es mostrado mediante síntesis de textura, al colocar repetidamente una muestra del tamaño del texel detectado sobre una superficie del mismo tamaño de la textura original y midiendo la semejanza entre la imagen sintetizada y la imagen original. Nuestro método muestra buenos resultados con texturas periódicas y semiperiódicas, pudiendo utilizarse en aplicaciones prácticas por su sencilla implementación.

Palabras clave: Procesamiento de Imágenes, Textura, Forma y Tamaño, Periodicidad de Textura, Entropía.

1 Introduction

Texture periodicity and texel size and shape estimation, are classical problems in the structural analysis of texture, since these parameters can be used to describe a texture in many applications. Texture is a visual property perceived in all objects around us, being an important characteristic for object discrimination. There is not a formal definition of visual texture, but from the structural point of view, it is widely accepted that the term generally refers to an image conformed by two components: a texture element (usually called texel), which is the fundamental micro-structure in generic natural images [Zhu et al, 2005], and its placement rules. The main task of structural analysis is to identify these elements, which are related with texture periodicity. These components are sought in order to obtain a compact description of a certain texture, which could be used in applications like texture synthesis [Djado et al. 2005; Dong et al, 2008], high speed image transmission, texture compression, among others. In the same way, the texel can be used as a structural reference in order to improve performance in classification tasks [Jan and Hsueh, 1998; Lizarraga-Morales et al, 2009] and segmentation [Todorovic and Ahuja, 2009] tasks and achieve invariant texture analysis [Kishor et al, 1995].

Texture periodicity, also called regularity, is one of the most important texture features in human perception [Tamura et al, 1978]. Texture periodicity is often measured in a regularity scale, ranging from periodic to stochastic. Nevertheless, real natural textures fall in-between these two extremes, considering them as near-periodic, or near-stochastic. Near-periodic textures can be viewed as periodic textures with statistical variations along different dimensions [Lin et al, 1997], i.e. variations in texel size, texel shape and placement rules over the field of view.

Co-occurrence matrix (CM) proposed by Haralick et al. (1973) has been a classical approach in texture analysis, and it is widely used to detect periodicity exploiting its parameterization, mainly using two statistics: χ^2 and κ. One of the first CM-based approaches is the proposed by Zucker and Terzopoulus (1980), where χ^2 statistics are used to find texture structure. χ^2 and κ statistics have been compared in complexity and accuracy for this task in [Selkainaho et al, 1988; Parkkinen et al, 1990] and [Starovoitov et al, 1998]. Other approaches have been proposed for the same task. Textural periodicity determination using a distance matching function has been proposed in [Oh at al, 1999], improving time consumption in comparison with inertias from the CM approach. While these methods are widely used, they have proven to be flawed in time consumption and in natural texture analysis due to imperfection in periodicity of these textures. It is not trivial to analyze natural textures since the periodicity is reduced by variations in elements as those indicated before, and others like illumination changes and perspective deformations, among others. Recently, Ahuja and Todorovic (2007) have proposed the extraction of texels in 2.1D natural textures using segmentation trees, but presenting execution time limitations for real-time application of this approach. Grigorescu and Petkov (2003), estimate the minimum square window that corresponds with texel size of regular images based on the calculation of Renyi's generalized entropies, having limitations with rectangular shaped texels. Other approaches and applications can be found in [Lin et al, 1999; Leu, 2001; Lee and Chen, 2002; Djado et al, 2005; Nang and Pang, 2009].

In this paper, texture periodicity and texel size are estimated using the property of entropy calculated from the Sum and Difference Histograms (SDH) proposed by Unser (1986). SDH have a free parameter, a relative displacement vector (DV) which consists in two components, horizontal and vertical. When DV is varied, an entropy function with respect to this parameter is obtained. When DV matches with the texel size or an integer multiple of it, entropy function reaches local minima. Such behavior allows us to detect period and hence, the texel size. In addition SDH present computational advantages over the CM-based approaches in complexity and memory consumption since SDH decrease in one order the CM-based approaches memory storage. The paper is structured as follows: Section 2 describes the computation of SDH. Section 3 describes the proposed method to extract the periodicity and texel size. Experiments and Results for artificial and natural textures with different randomness levels are presented in Section 4. Finally, a summary and the conclusion are given in Section 5.

2 Sum and Difference Histograms

To obtain the sum and difference histograms, let us define an image I of $M \times N$ pixels size, and K gray levels $k = \{0, 1, \ldots, K-1\}$. Consider a pixel localized in coordinates (m, n) with intensity denoted as $I_{m,n}$ and a second pixel in the relative position $(m + d_m, n + d_n)$ with intensity $I_{m+d_m,n+d_n}$, where (d_m, d_n) is the relative displacement vector (DV). Sums and differences of pixels associated with the relative DV (d_m, d_n), are defined as:

$$s_{m,n} = I_{m,n} + I_{m+d_m,n+d_n}, \qquad (1)$$

$$d_{m,n} = I_{m,n} - I_{m+d_n,n+d_n}. \qquad (2)$$

Sum histogram h_s and difference histogram h_d with displacement vector (d_m, d_n) over the image domain *D*, are defined as:

$$h_s(i) = Card\{(m,n) \in D, s_{m,n} = i\}, \qquad (3)$$

$$h_d(j) = Card\{(m,n) \in D, d_{m,n} = j\}. \qquad (4)$$

The total number of counts in histograms is:

$$A = \sum_i h_s(i) = \sum_j h_d(j). \quad (5)$$

Normalized sum and differences histograms are estimates of the sum and difference probability functions defined by:

$$P_s(i) = \frac{h_s(i)}{A}; \qquad (i = 0, \ldots, 2K-2), \quad (6)$$

$$P_d(j) = \frac{h_d(j)}{A}; \qquad (j = -K-1, \ldots, K-1). \quad (7)$$

Unser (1986) suggested the use of SDH to compute a subset of the textural features previously proposed by Haralick et al. (1973) in order to simplify the computation. Five of those measures are:

$$\text{entropy} = E = -\sum_i P_s(i) \cdot log(P_s(i)) - \sum_j P_d(j) \cdot \quad (8)$$

$$\text{energy} = F = \sum_i P_s(i)^2 \cdot \sum_j P_d(j)^2, \quad (9)$$

$$\text{homogeneity} = G = \sum_i \frac{1}{1+j^2} \cdot P_d(j), \quad (10)$$

$$\text{mean} = \mu = \frac{1}{2} \sum_i i \cdot P_s(i), \quad (11)$$

$$\text{contrast} = C = \sum_j j^2 \cdot P_d(j)^2. \quad (12)$$

In this work, the measure used is the entropy, defined in Eq. 8. In order to get an estimation of the texel size of visual textures, we use an entropy measure with different displacement vectors associated. When a periodic texture pattern is analyzed with a DV with length of one period in any direction, differences $d_{m,n}$ only take values of zero, as the reference pixel $I(m,n)$ and the relative pixel $I(m+v_m, n+v_n)$ have the same intensity values. When the difference histogram has only one bin filled, the second part of entropy equation is zero, reaching a minimum value depending of the texture gray levels.

3 Periodicity and Texel size Estimation

Periodicity is the quality of being regularly recurrent in a certain interval. Any function $f(t)$ with domain D_f is periodic with period T if it satisfies the condition:

$$f(t) = f(t+T), \qquad \forall t : t, t+T \in D_f. \quad (13)$$

Texture periodicity can occur in two directions, vertical and horizontal. Texture patterns that satisfy the condition presented in Eq. 13 can be considered periodic with horizontal and vertical periods T_m, T_n (measured in pixels). Texel size is obtained by joining the two periods, $T_m \times T_n$ pixels.

As previously said, SDH are parameterized by a displacement vector which is represented as $DV = (d_m, d_n)$. Let us consider the periodic texture I previously described, with dimensions of $M \times N$ pixels and periods T_m, T_n in horizontal and vertical directions, respectively. Using SDH we can obtain an entropy value $E(DV)$ in function of the displacement vector $DV = d_m, d_n$. In a periodic texture, when DV matches the texture period (texel size), or multiples of it, entropy function reaches a minimum value, we propose to search the value of DV in the field of view for which entropy function reaches the local minima. Vertical period is found when $d_m = 0$ and d_n takes values in the range $[2, \frac{N}{2}]$. Similarly, horizontal period is found when $d_n = 0$ and d_m is varied in the range of $[2, \frac{M}{2}]$. The upper values of $\frac{M}{2}$ and $\frac{N}{2}$ are proposed to assure at least two texels on the visual texture under analysis.

As an example of this method, let us consider an artificial and periodic texture image of 256×256 pixels comprising a texel size of 60×39 pixels (Fig. 1). We have computed the entropy measure for both directions, horizontal and vertical (shown in Fig.1, marker o is used for horizontal direction values and marker **+** is used for the vertical direction values). We can see that entropy plots present global minima values at the corresponding texel size multiples, 60 and 120 for horizontal detection and 39, 78 and 117 for vertical detection.

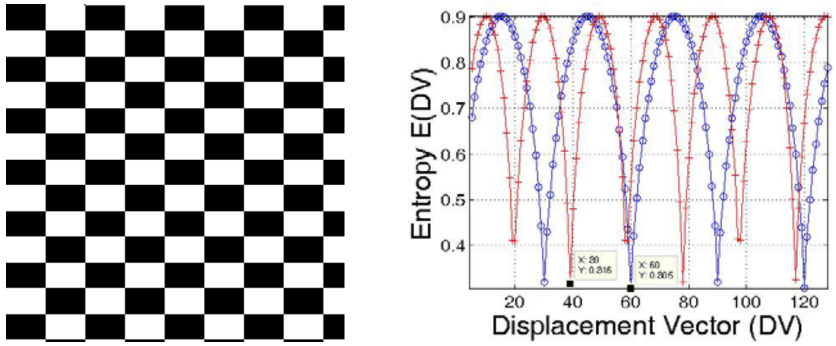

Fig. 1. An artificial and periodic texture pattern and its entropy function in both directions

4 Experiments and Results

In this section, we present two experiments to validate our approach. In the first experiment, we use artificial images under noise conditions and in the second experiment, we use natural images.

4.1 Texel Size Estimation in Artificial and Periodic Texture Patterns with Noise

In order to evaluate the performance limits of the proposed approach, we have corrupted the artificial and periodic texture pattern from Fig. 1 with different occupancy percentages of salt and pepper noise. Occupancy percentages of noise are 0%, 10%, 20%, 40%, 60%, 80% and 90%. In this image, we know that the texel size is of 60 x 39 pixels size, and with the different noise levels, we can know the boundaries of our approach. Results of these experiments are shown in Fig. 2. This figure presents each of the images with different noise occupancy levels and the texel estimated. Noise occupancy of 0% was obviated, and we show the other 6 images with texel size estimated in pixels. As we can see in Fig. 2 our approach detects the correct texel in cases of 10%, 20%, 40% and 60%.

4.2 Texel Size Estimation of Natural Near-Periodic Images

Natural images can be considered as textures with both noise and placement rule variations, thus presenting a challenge for any texture analysis system. We have evaluated performance of our approach using near-periodic natural images. Texel size of a periodic texture pattern is estimated by finding the first global minimum, but it is more difficult when a natural texture is analyzed. Changes in texel shape and its placement rules reduce periodicity due to the typical irregularities over natural surfaces. Let us take the natural texture pattern shown in Fig. 3, whom texel size is approximately 41 x 17 pixels size. By analyzing this texture pattern with our method, we obtain the entropy functions, also shown in Fig. 3. Although functions are not periodic, they still have local minima when DV corresponds with the texel size. With natural texture images, we say that texel size is estimated by the DV where the global minimum from entropy functions is found.

To test the performance of our approach, we use 25 images. The image data set (see Fig. 4) consists of an artificial texture and 24 images extracted from the albums [Brodatz, 1966] and the suggested by Klette (2009). At a first glance, these textures seem to be periodic. Nevertheless, a thorough inspection shows that their periodicity descriptors (texel size, shape, gray-levels and placement rules) vary, because of the image natural origin. We take these images as good examples of near-periodic textures. For all the set, we have obtained an estimation of the texel size by using our method. For each image, results are presented in Table 1.

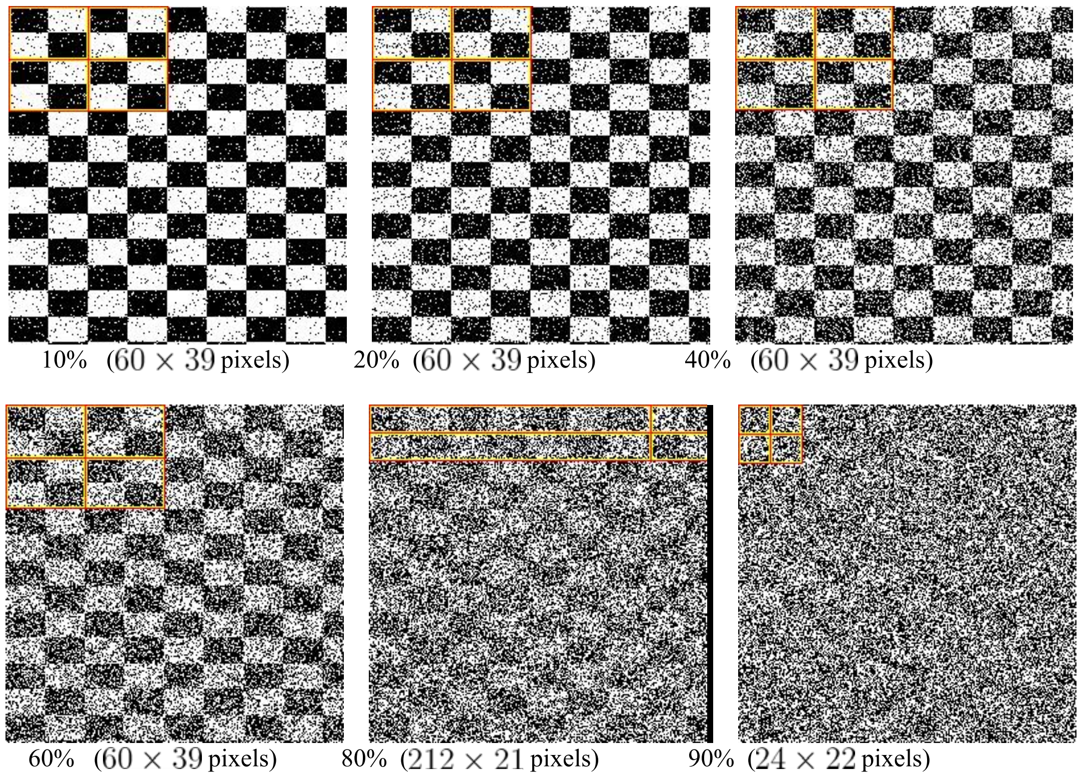

Fig. 2. Results of an artificial and periodic texture pattern with different noise occupancy levels, highlighting the texel size detected

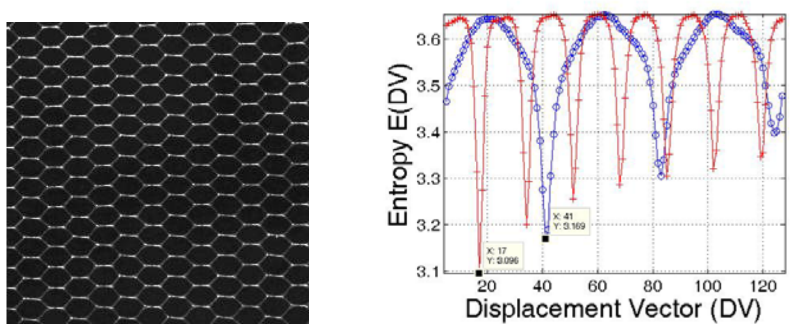

Fig. 3. A natural near-periodic texture pattern and its entropy function in both directions

In order to evaluate the accuracy of the texel estimated, we have taken a sample from the original image and used it in texture synthesis. Texture synthesis is an important issue in computer vision, used to verify texture analysis methods among other applications. The algorithm used in this experiment for synthesis is the tiling algorithm. Such algorithm consists in tiling an image with specific dimensions where the tile is a sample of a given texture. In this experiment, the tile is the first sample of the corresponding texel taken from the original image.

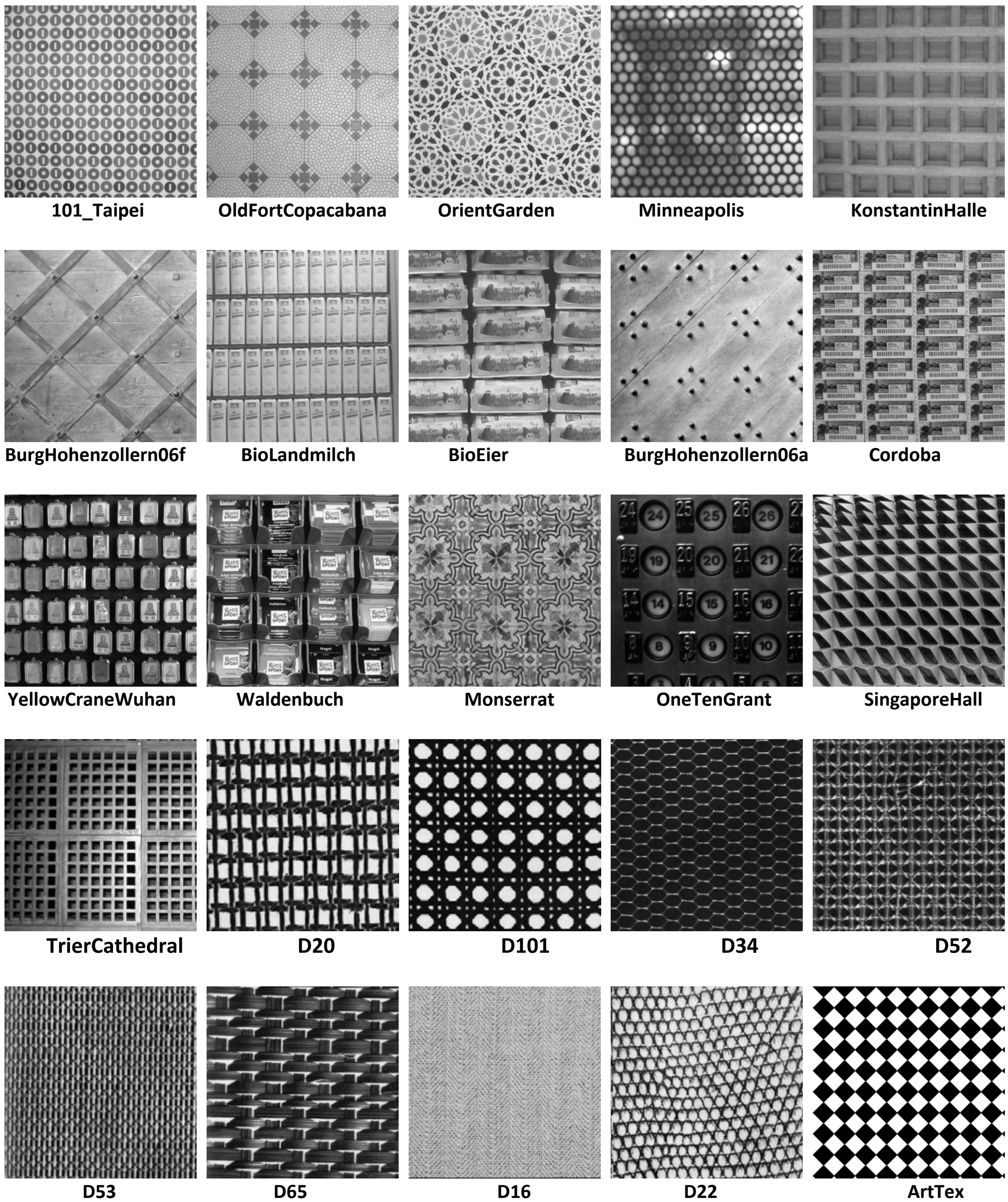

Fig. 4. Natural images set used in experiments

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Example results for five images from Fig. 4 are shown in Fig. 5. Such results correspond to texel estimation and texture synthesis. In this figure, each row presents 3 images; first column presents the original image with the texel size estimated marked twice in each direction. Second column presents entropy plots for both directions horizontal (marked with o) and vertical (marked with +), in this plot, global minima are labeled. Finally, results of synthesis with the tiling algorithm are shown on the third column of each row.

In order to quantify the similarity between the original image and the synthetic image, we use the cosine similarity metric defined in Eq. 14. Cosine similarity metric is a common vector similarity measure. Whereby the input vector is transformed into vector space so that the Euclidean cosine rule can be used to determine similarity, and guarantees, as do other similarity metrics, that $0 \leq cos(h_1, h_2) \leq 1$, so we can have an intuitive result where 1 is the value for two images that match exactly. Cosine similarity metric is computed as:

$$cos(h_1, h_2) = \frac{\sum_k h_1(k) h_2(k)}{\sqrt{\sum_k h_1(k)^2 \sum_k h_2(k)^2}}, \qquad (14)$$

where h_1 and h_2 are two histograms, with k gray-levels.

Synthesis algorithm consists in taking the first sample of the size detected and repeating this sample in both horizontal and vertical direction through a specific surface. Results of cosine similarity metric are shown in Table 2. These values show that the synthetic image is very similar to the original one with an average value of 0.890377 (89% similar). We can see that the artificial texture named as ArtTex, matches exactly with the original one obtaining a value of 1.0. Synthetic images corresponding with Orient Garden, Bio Land milch, Burg Hohenzollern, Yellow Crane Wuhan, Monserrat, One Ten Grant, D20, D101, D52, D65, D16 and D22, exhibit good similarity values, higher than 0.9, this is, images are similar in more that 90%. The lowest value of 0.635862 (marked in Table 2 in bold) is obtained with the image 101_Taipei, where the tiling algorithm fails, because of the rotation in the natural image, even if the texel size is correctly determined. Resulting images corresponding to the best result and with the lower one are shown in Fig. 6, where the entropy functions in both directions and the resulting synthesized image are also shown. In general, there are certain differences between the original and synthetic images, due to natural irregularities of texture. There is an error that accumulates and propagates over the entire synthetic surface because of the regularity of the tiling algorithm, since it is unable to synthesize these natural irregularities.

Table 1. Texel size estimation for textures in Fig. 4 using an entropy measure

Texture	**Texel Size**
101_Taipei	58x58
OldFortCopacabana	115x116
OrientGarden	194x199
Minneapolis	27x47
KonstantinHalle	81x78
BurgHohenzollern06f	180x177
BioLandmilch	36x113
BioEier	181x78
BurgHohenzollern06a	126x127
Cordoba	117x47
YellowCraneWuhan	52x71
Waldenbuch	113x109
Monserrat	152x153
OneTenGrant	125x97
SingaporeHall	47x40
TrierCathedral	26x26
D20	33x33
D101	38x37
D34	17x41
D52	59x32
D53	20x14
D65	28x69
D16	7x43
D22	83x109
ArtTex	28x28

Table 2. Results of cosine similarity metric between original image and synthesized texture

Texture	Cosine Similarity	Similarity Percentage
101_Taipei	***0.636***	***63.6%***
OldFortCopacabana	0.780	78.0%
OrientGarden	0.967	96.7%
Minneapolis	0.880	88.0%
BurgHohenzollern06f	0.846	84.6%
BioLandmilch	0.948	94.8%
BioEier	0.887	88.7%
BurgHohenzollern06a	0.947	94.7%
Cordoba	0.719	71.9%
YellowCraneWuhan	0.973	97.3%
Waldenbuch	0.895	89.5%
Monserrat	0.923	92.3%
OneTenGrant	0.917	91.7%
SingaporeHall	0.809	80.9%
TrierCathedral	0.799	79.9%
D20	0.915	91.5%
D101	***0.990***	***99.0%***
D34	0.877	87.7%
D52	0.982	98.2%
D53	0.805	80.5%
D65	0.956	95.6%
D16	0.964	96.4%
D22	0.953	95.3%
ArtTex	1.000	100.0%
Total Average	***0.890***	***89.0%***

5 Summary and Conclusion

Periodicity and texel size detection are classical problems in structural texture analysis. In this paper, the use of the entropy measure obtained from the sum and difference histograms to detect period in periodic, noise corrupted periodic and near-periodic textures, has been discussed. Entropy measure is proposed to be used as a function of the displacement vector, which is the free parameter of the sum and difference histograms. When a displacement vector matches the texel size or its multiples, the entropy function reaches local minima, but texel size is found on the displacement vector where the global minimum is found. Textures have been analyzed in two directions, horizontal and vertical, in order to find periodicity in both directions. Performance has been evaluated over artificial textures, where our method has shown tolerance to salt and pepper noise. Our method has been also evaluated over natural near-periodic textures. Qualitative evaluation with texture synthesis by tiling has been implemented. Similarity between synthesized image and original image has been measured, obtaining average similarity of 89% using a cosine similarity metric.

The main advantage of this method over the ones based on the CM is the use of the SDH that simplifies the computational complexity and memory storage. In an image with K grey levels, the CM requires $K \times K$ memory locations, while the SDH only requires $2K - 1$ for each histogram. Another advantage is the analysis in two directions by fixing to zero a component of the DV. Doing so, we can detect different shapes of texels, accurately identifying a square or rectangular texel. This approach, yet simple in its implementation is fast enough to be considered for practical applications, either texture synthesis or texture analysis.

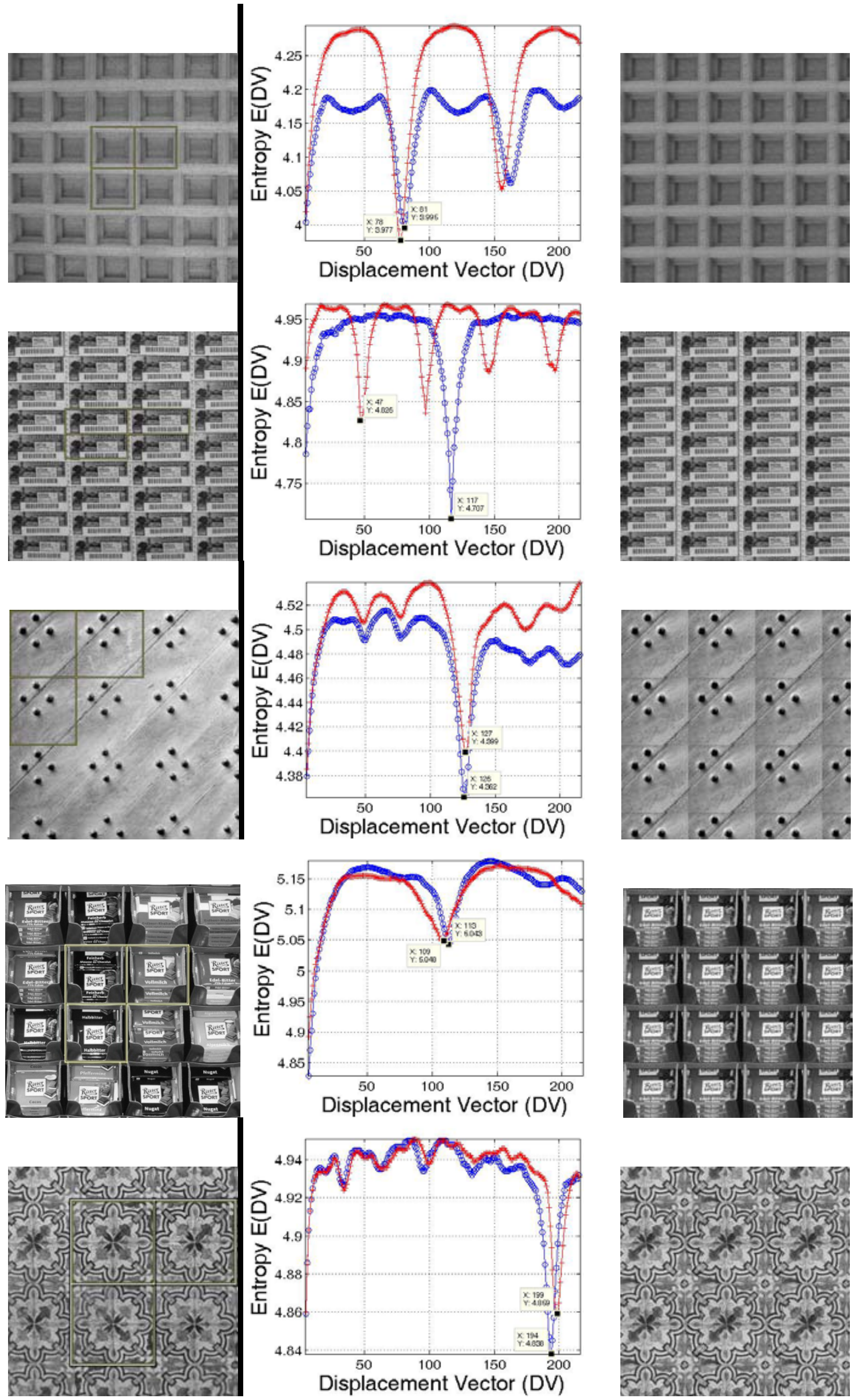

Fig. 5. Examples of Results. Original image, corresponding entropy plots and synthesized image

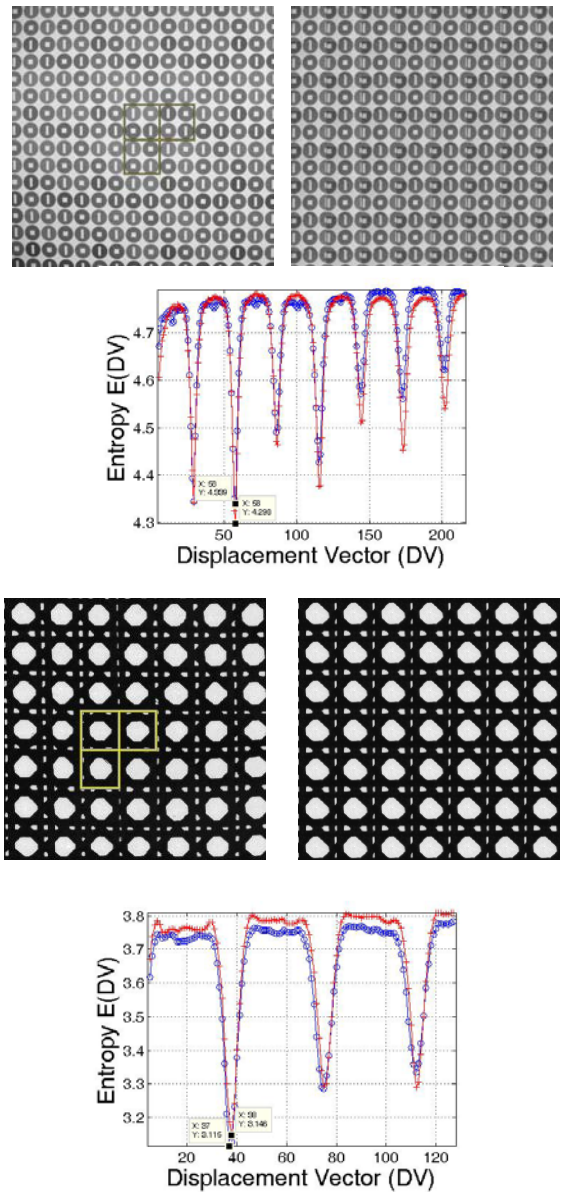

Fig. 6. Original image with texel marked, texture synthesized and entropy plots for the lowest (top) and highest (bottom) cosine similarity metric

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