A NO-REFERENCE PERCEPTUAL TEXTURE REGULARITY METRIC

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ABSTRACT

This paper presents a no reference perceptual metric that quantifies the degree of regularity in textures. The metric is based on the probability of visual attention at each pixel of the texture image, similarity of visual attention of the textural primitives and the periodic spatial distribution of foveated fixation regions throughout the image. It is shown through subjective testing that the proposed metric has a strong correlation with the Mean Opinion Score for the regularity of textures.

Index Terms— Visual Attention, Texture Analysis, Randomness, Image Quality Assessment

1. INTRODUCTION

Textures on natural and man-made objects have served as an important visual cue for the recognition, segmentation and classification of these objects. The analysis of the inherent properties of textures plays a significant role in many applications such as content-based image retrieval [1], defect detection on fabrics [2] and texture synthesis [3]. A texture can be characterized using a collection of image primitives [4]. These primitives can exhibit varying degrees of regularity in their spatial placements, size, shape, tonal properties, directionality and granularity as shown in Fig. 1. The overall perceptual regularity of textures is due to the accumulated effect of all these factors and this paper aims to measure the degree of this regularity. The motivation for this metric comes from its compelling potential impact on unsupervised image processing applications. The proposed metric can hasten the process of texture classification and image retrieval applications. In texture synthesis, it can guide the application of the appropriate synthesis method on a "seed" texture [3]. In texture analysis, it can aid in applying the correct models.

Many approaches have been proposed in the past to quantify the regularity or randomness of textures. A measure of spatial periodicity for regular textures, derived from the Gray Level Co-occurrence Matrix (GLCM) is proposed in [4]. A faster version of this approach that acts on a Binary Co-occurrence Matrix is proposed in [5]. A 2D Wold decomposition of homogeneous random fields is employed in [6] to extract the periodic, random and directional components of textures. In [7], the spatial regularities in the pixel intensities and the placement of the primitives along a direction, together quantify the directional regularity. The overall regularity metric is taken as the maximum of the directional regularities. In [8], the randomness of the observed texture is represented by a Kolmogrov Stochasticity parameter measured between the empirical and a modeled distribution of wavelet packet coefficients.

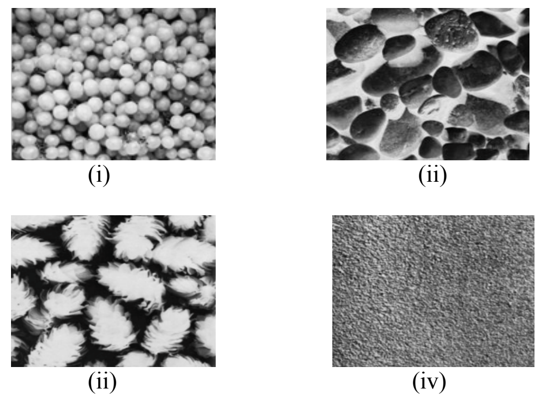
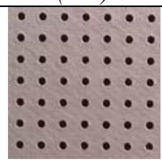
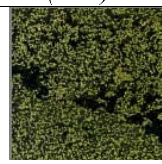
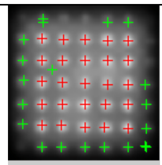
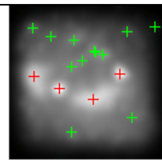
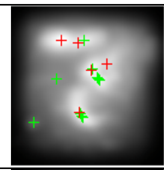
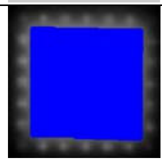
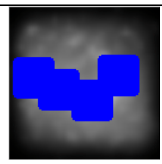
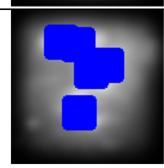
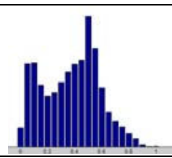
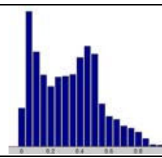
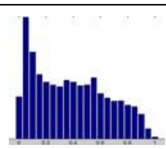


Fig. 1:Examples of irregularity in textures due to (i) placement (ii)size, shape or color(iii) directionality and (iv) fine-granularity of primitives

None of the above mentioned approaches take human perception into account but directly operate on the pixel domain [5] or on the spectral domains [9]. When we look at textures, we don't concentrate on individual pixels but at visually salient regions. This is ignored by the pixel-based periodicity approaches. Some of the approaches like [2], assume that they act on a patterned regular texture and are thus not suitable for stochastic textures. Perceptual quality metrics for textures proposed in the past like STSIM[10], are full reference metrics used to assess distortions in a texture with respect to a reference, and cannot quantify the structure in a newly observed texture without the presence of a reference. Furthermore, they cannot assess the degree of regularity in a texture image. A rarity-based VA model for texture description is suggested in [11]. The method classifies the regions of an image into regular and irregular textures by considering irregular texture regions to be highly salient relative to regular texture regions. However, this assumption does not generally hold since regular textures can also be highly salient (Table 1).

Table 1. Visual saliency for regular and irregular textures.

	Regular Texture *(Tile)*	Irregular Texture *(Misc)*	Irregular Texture*(Clouds)*
Texture			
Saliency Map with Peaks red- strong green-weak			
Saliency Map with Foveated Fixation Regions			
Histogram of the Saliency Map			

In this paper, we propose that the perceived regularity in a texture is manifested in the spatial distribution of visually salient points over it. We also propose a texture-regularity metric based on the characteristics of the visual saliency map.

This paper is organized as follows. The proposed texture regularity metric is described in Section 2. Performance results are presented in Section 3 followed by a conclusion in Section 4.

2. PROPOSED METHOD

When viewing a visual scene, the human visual system fixates on salient points in that scene. This visual attention can be captured through a Visual Saliency Map (VSM) whose values directly quantify the extent to which each region grabs the human attention. The saliency map is normalized to 1 and shown as an image in which the brightest pixels (close to 1) correspond to highest attention and the darkest pixels (close to 0) correspond to lowest attention. Table 1 shows sample regular and irregular textures (row 1) and their corresponding VSM maps (row 2). The red crosses indicate visually significant large peaks while the green crosses correspond to smaller less significant local peaks. As illustrated in Table 1 (rows 1 and 2), the VSM characteristics differ between regular and irregular textures. This fact can be exploited in quantifying the degree of regularity of a texture image. Table 1 also shows the normalized histograms of the VSMs. Each normalized histogram, *P(VA)*, corresponds to the probability of an attention level *VA* (VSM value) occurring in the associated texture image. An attention level $VA <= 0.5$, corresponds to a low attentive area.

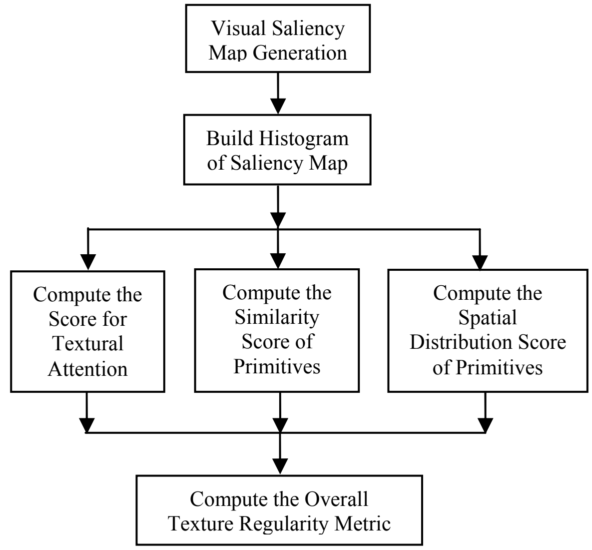


Fig.2. Block diagram of the proposed metric.

Fig 2 shows a flowchart of the proposed texture regularity metric computation algorithm. The proposed algorithm makes use of the VSM characteristics and distribution in order to assess the degree of regularity in texture images. In our implementation, the VSM is generated using the GBVS model[12]. More details about each of the stages are given in Sections 2.1 to 2.3.

2.1 Score for Textural Attention

Let *VA_Thresh* denote the visual attention threshold. A location is considered to be highly salient if its associated attention level *VA>=VA_Thresh*. The last local peak of the VSM histogram, *lpeak* is used to determine the visual attention threshold, *VA_Thresh* as follows:

$$VA\_Thresh \;=\; \begin{cases} lpeak, & if \quad 0.5 \le lpeak \le 0.65 \\ 0.6, & Otherwise \end{cases} \qquad (1)$$

All pixels having an attention level greater than *VA_Thresh* are very much noticeable and give a pattern and structure to the texture. This is quantified as the score for textural attention which is given by:

$$S_{attention} \;=\; \sum_{VA \ge VA\_Thresh}^{1} P(VA) \qquad (2)$$

where *P(VA)* is the probability of visual attention obtained from the normalized histogram of the VSM. In the case of a regular texture, the last peak of the histogram tends to fall between 0.5 and 0.65 and the total probability of visual attention beyond the *VA_Thresh* (corresponding to the proportion of image occupied by the primitives) is relatively large as compared to an irregular texture. In the case of nonregular textures, the last peak tend to occur at a much smaller value below 0.5, and the total probability above *VA_Thresh* tend to be relatively small.

2.2. Similarity Score for textural primitives

Within each primitive, visual attention is largest at the center and decreases from the center to the periphery. The high VA values in the tail of the histogram (following the last peak *lpeak*) correspond to the central primitive pixels which are few in number. The *lpeak* location value corresponds to the VA for the peripheral primitive pixels which are larger in number. When the texture primitives are identical in size, shape and color, the central and peripheral pixels of one primitive would have, respectively, the same visual attention levels as the corresponding pixels of another primitive. This gives a sharp decay of the histogram beyond the last peak. In the case of textures with irregularly shaped, sized or colored primitives, the visual attention values at the peripheral regions of the primitives are not identical to each other. Hence, the last peak of the histogram is relatively smaller and there is a spread of higher VA values. This leads to a gradual decay of the histogram. The decay rate of the histogram is found by fitting an exponential function to the tail of the histogram as follows:

$$(a,b) = \arg\min_{a,b}\left(\sum_{VA>=lpeak}^{1}\left(P(VA)-a*e^{-b.VA}\right)^{2}\right) \quad (3)$$

The decay parameter $b$contributes to the quantification of the texture regularity and is used in computing the similarity score as follows:

$$S_{similarity} = \min(b, \max\_b) / \max\_b \quad (4)$$

where max_b is used to saturate the decay to a maximum value and to normalize the similarity score to the range [0,1]

2.3. Spatial Distribution Score for Textural Primitives

The above mentioned scores quantify the proportion of visually attentive pixels and the similarity between the primitives as measures of regularity. But even when these two scores are high, regularity falls when the primitives are not spatially distributed in a periodic or quasi-periodic manner and do not span the entire image. A spatial distribution score is attributed to the texture for this purpose. The peaks in the VSM, which act as local maxima, are first located. Then, for each peak p_i, the distance of its closest neighboring peak, $cdist_i$, is found:

$$cdist_i = \min(p_i - p_j), \text{ where } 1<=i,j<=N \text{ and } i \neq j \quad (5)$$

The standard deviation of the computed distance values,$cdist_i$, is higher for textures with irregularly placed primitives and lower for regularly placed primitives. The standard deviation of $cdist_i$, $std(cdist_i)$,is used to compute the placement regularity score as follows:

$$S_{placement\_regularity} = 1 - \frac{std(cdist_i)}{\max\_std}, \text{ where } 1 \le i \le N \quad (6)$$

where max_*std* is used to saturate $std(cdist_i)$ to a maximum value and to normalize the placement regularity score to the range [0,1].

In addition, a score characterizing the spread of the primitives is computed as follows. The located VSM peaks act as foveation centers and a foveated region, approximated by a block of size $L\times L$ ($L\cong$ 65 for our viewing set-up), is assigned around each peak. The union of all these regions gives a measure of the spread of the texture primitives. The higher the spread, the higher is the perceived regularity. A texture spread score is thus computed as follows:

$$S_{texture\_spread} = \frac{Foveation\ \ Area}{Total\ \ Image\ \ Area} \quad (7)$$

where

$$Foveation\ \ Area = \bigcup_{1<=i<=N} r(m-x_i, n-y_i) \quad (8)$$

In (8), (x_i,y_i) is the location of the peak p_i and $r(m.n)$ is given by:

$$r(m,n) = \begin{cases} 1, & -(L-1)/2 \le m,n \le (L-1)/2 \\ 0, & \text{Otherwise} \end{cases} \quad (9)$$

where L is the width of a foveated region.

The spatial distribution score is then computed as follows:

$$S_{spatial\_distribution} = S_{placement\_regularity} \cdot S_{texture\_spread} \quad (10)$$

The overall texture regularity measure is obtained as follows:

$$S_{regularity} = S_{attention}^{\alpha_1} \cdot S_{similarity}^{\alpha_2} \cdot S_{spatial\_distribution}^{\alpha_3} \quad (11)$$

In (11), the values $\alpha_1 = 1$, $\alpha_2 = 2$ and $\alpha_3 = 1$ were used.

3. SIMULATION RESULTS

A subjective testing was conducted on 21 textures from two databases, namely, MIT Vistex database [14] and Graph-Cut texture synthesis database[15]. Ten subjects with normal to corrected vision participated in the subjective tests. The textures, equally distributed amongst the broad classes of regular, irregular or hybrid textures, were randomly displayed one after another to each subject. The subjects were asked to score the overall regularity for each observed texture, using a three-scale score with 1 corresponding to lowest and 3 to highest. In addition to observing the overall texture regularity, subjects were asked to observe and score using a three-scale score (1 being the lowest and 3 the highest) five visual properties of the texture primitives before indicating their final overall regularity score for each displayed texture image, namely (i) ease in locating the primitive, (ii) regularity in the placement of the primitives, (iii) regularity in size, shape and color of the primitives, (iv) regularity in the direction of the primitives, and (v) average

Table 2. Mean Opinion Score (MOS) and the proposed metric for textures in the decreasing order of regularity.

Texture Image	MOS Average Property	MOS Overall Regularity	Texture Regularity Metric (100x)
Tile.ppm	2.825	3.000	8.4605
marbles.jpg	2.813	3.000	8.3111
keyboard.jpg	2.788	2.813	3.1157
maille.jpg	2.713	2.813	4.2183
gecko.jpg	2.675	2.875	2.4281
horses.jpg	2.638	2.688	1.5890
puzzlepieces.jpg	2.525	2.688	1.7515
cream.jpg	2.425	2.875	0.8421
bricks.jpg	2.425	2.625	0.9894
red-peppers.jpg	2.175	2.313	2.6422
tulips.jpg	2.013	2.000	1.3118
freshblueberries.	1.925	2.000	0.7251
tomatoes.jpg	1.850	2.125	1.1574
lobelia.jpg	1.775	2.000	0.4717
Flowers.ppm	1.750	1.938	0.4089
rice.jpg	1.713	1.875	0.2307
Clouds.ppm	1.375	1.125	0.1108
long_island.jpg	1.325	1.188	0.0427
northbeach.jpg	1.275	1.313	0.0382
Misc.ppm	1.175	1.313	0.3599
Water.ppm	1.163	1.250	0.0864

size of the primitives. The primitives in a regular texture are very easy to find compared to those in an irregular texture. Also, small sized primitives are perceived as less regular than larger ones [4]. An average of the five property scores gives the "Average Property" score for each subject. The Overall Regularity and the Average Property scores were separately averaged over all 10 subjects to generate the respective Mean Opinion Scores (MOS Property Regularity and MOS Overall Regularity) as shown in Table 2. The proposed regularity metric lies in the ranges of 0 to 1. To represent very small decimals the metric is scaled by a factor of 100 and shown in Table 2. To account for extreme values at the ends of the testing range (very high and very low regularity), each metric value M_i is transformed into a predicted MOS (MOS_{pi}) value using a four-parameter logistic function as suggested by VQEG[13]:

$$MOS_{p_i} = \frac{\beta_1 - \beta_2}{1 + e^{(M_i - \beta_3 / |\beta_4|)}} + \beta_2 \qquad (12)$$

Table 3. Correlation of the proposed metric with MOS.

Texture Set	MOS	PLCC	SROCC	RMSE	MAE
All 21 Textures	Overall Regularity	90.63	89.64	0.269	0.207
	Average Property	92.15	93.86	0.222	0.167
Without Outliers	Overall Regularity	95.54	96.08	0.194	0.155
	Average Property	96.05	96.28	0.168	0.127

The performance of the proposed Texture Regularity Metric to quantify the perceived regularity is shown through the Pearson Linear Correlation Coefficient (PLCC) and the Spearman Rank Order Correlation Coefficient (SROCC) between MOS_p and MOS. As shown in Table 3, for the original set of 21 textures, the metric results in a PLCC of 90.6 % and SROCC of 89.6% for the Overall Regularity MOS. The PLCC and SROCC values are 92.1% and 93.8%, respectively, when correlating the metric with the Average Property MOS. Table 3 also shows the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) of the metric in predicting the MOS. As seen in Table 2, *bricks, cream* and *red-peppers* are the outliers. The metric failed to predict the regularity on tiled textures like bricks and cream due to the inability of the employed visual attention model (GBVS [12]) to generate the appropriate saliency map for these textures. In the case of *red-peppers*, the high similarity in tonal properties between the primitives caused a high value for the metric. But the MOS scores were medium for this case due to irregularities in shape of primitives. As shown in Table 3, when eliminating these outliers, the PLCC and SROCC with the Overall Regularity MOS increases to 95.5% and 96.1%, respectively, for the remaining 18 textures.

4. CONCLUSION

A novel no-reference texture regularity metric based on the visual attention of textures, is proposed in this paper. The proposed metric is based on characteristics that are extracted from the visual saliency map and its distribution in order to predict the regularity of textures as perceived by human subjects. The regularity metric can be further improved by applying better visual attention models that more closely predict the true human visual saliency on textures.

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