Quality Assessment of Fractalized NPR Textures: a Perceptual Objective Metric

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Abstract

Texture *fractalization* is used in many existing approaches to ensure the temporal coherence of a stylized animation. This paper presents the results of a psychophysical user-study evaluating the relative distortion induced by a *fractalization* process of typical medium textures. We perform a ranking experiment, assess the agreement among the participants and study the criteria they used. Finally we show that the average co-occurrence error is an efficient quality predictor in this context.

CR Categories: I.4.7 [Image processing and Computer Vision]: Feature Management—Texture

Keywords: texture, perceptual evaluation, non-photorealistic rendering

1 Introduction

Many non-photorealistic rendering approaches aim at depicting 3D scenes with styles that are traditionally produced by 2D media (pigments, strokes...). The main problem of these methods is the lack of *temporal coherence* while stylizing dynamic scenes. It results from the conflicting goals of depicting a 3D motion while preserving the 2D characteristics of the medium: in particular, screen-space size and stroke density. Several approaches represent this medium as a texture and partially solve the problem of temporal coherence via a *fractalization* process that combines many versions of the original texture at different scales through alpha-blending (e.g., [Klein et al. 2000; Cunzi et al. 2003; Breslav et al. 2007; Bénard et al. 2009]).

However, these solutions modify the patterns in the texture: new features and new frequencies may appear, global contrast may be degraded and deformations may occur. As a result the *fractalized texture* is likely to be visually dissimilar to the original texture targeted by the artist. We believe that the automatic evaluation of this similarity loss can be a valuable tool for comparing existing alpha-blending approaches and may allow the development of new *fractalization* techniques. This problem is particularly challenging in NPR because the assessing the modification of appearance involves multiple factors and perceptual effects.

In this context, we define the texture *distortion* as the dissimilarity between the original and transformed 2D texture. Our goal is to define a quantitative metric for this distortion in two steps. For that, we perform a study in which users are asked to rank pairs of original/distorted textures from the least distorted pair to the most distorted pair. We provide a statistical analysis of the results to derive perceived quality scales for ten classes of NPR media. In this study, we deliberately avoid giving an explanation of the nature of the transformation. We ask the participants themselves to identify the criteria they have used to assess the distortion. In a second step, we study the correlation of these subjective results with several objective metrics that are coming from image quality assessment and texture analysis, and based on global and local image statistics or spectrum analysis. We suggest that the *average co-occurrence error* (ACE) is a good predictor of the distortion.

This work is a first step toward the quantitative evaluation of the perceived effects of *fractalization* as we only focus on a bi-dimensional (without perspective projection) and static (a single image) study. This restricted scenario is still of interest though, as it corresponds to slow motions or still frames of an animation.

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2 Previous Work

Perceptual experiments take a growing part in computer graphics. Three main indirect methodologies exist for deriving psychophysical scales: rating, paired comparison and ranking. In the following we present an overview of these main approaches.

Rating consists in estimating statistical metrics (root mean square, Pearson correlation and outlier ratio) between the objective model output and the results from viewer subjective rating of the test images. This is the usual setup in image and video quality assessment [Sheikh et al. 2006; Winkler 2005]. The validity and reliability of rating data can only be asserted considering very large number of trials and participants have to be trained before the trial [Kendall 1975].

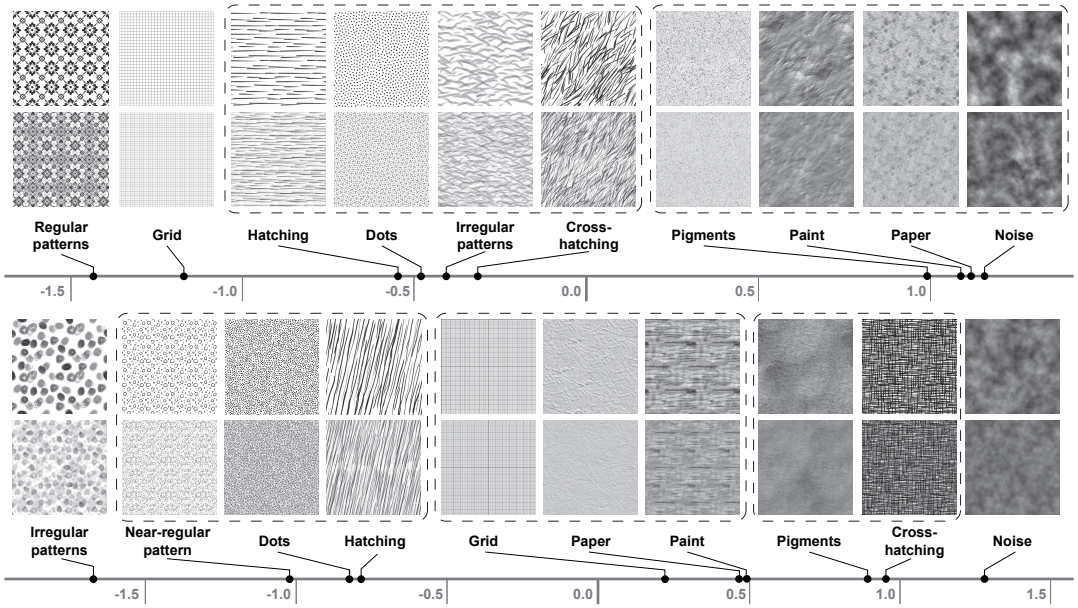
Paired Comparison In this setup, the whole dataset is presented pair by pair to the user who has to make straightforward forced choices. This approach was used to compare the performances of tone mapping operators [Ledda et al. 2005; Čadík et al. 2008]. Its main limitation is its quadratic complexity. In our case it would mean asking for ninety comparisons, making the experiment tiresome for users.

Ranking uses images organized according to a certain varying degree of quality [Guilford 1954]. Hence, this setup is the least time consuming one while it still provides for relevant data and is more appreciated by participants in general. Stokes et al. [2004] run a series of ranking experiments to define the perceptual importance of different illumination components for efficient high quality global illumination rendering.

Considering its advantages, we use the ranking methodology for our user study. Our work deals with texture transformation for NPR. In this field, perceptual evaluations have been proposed for specific styles, using different methodologies [Santella and DeCarlo 2004]. Among them, Isenberg et al. [2006] conduct an observational study to evaluate how people assess both hand-made stippling illustrations and computer-generated ones. Then, they perform a statistical analysis [Maciejewski et al. 2008] using gray-level co-occurrence matrices (GLCM) to compare the correlation between the different techniques. We take inspiration of this approach to derive an objective distortion metric.

3 Experimental Framework

Our goal is to define some estimate of the quality of NPR renderings based on *texture fractalization*. For that, we design a ranking experiment and derive an interval scale of perceived distortion to which we correlate an objective metric.



(a) *First (top) and second (bottom) texture pairs sets. For each series, the first row corresponds to the undistorted original textures, while the second depicts their fractalized versions.*

	Pigments	Dots	Hatching	Cross-hatching	Grid	Paint	Paper	Reg. patterns	Noise	Irr. patterns
S_1	0.9936	-0.4810	-0.5487	-0.3167	-1.1725	1.0903	1.1193	-1.4336	1.1580	-0.4085
S_2	0.8921	-0.82544	-0.7848	0.9552	0.2204	0.4909	0.4683	-1.0238	1.2798	-1.6729

(b) *z-Scores of the two series.*

Figure 1: *(a) The two series of medium texture pairs*[1] *in decreasing order of perceived distortion. These intervals scales are derived from the z-Scores shown in (b). Texture pairs surrounded by the same dashed line may be considered as perceptually equivalently distorted.*

3.1 Stimuli

We choose twenty gray-scale 2D textures sufficiently representative of the main traditional media used in NPR[1]. To create a sufficient redundancy in the results, we design two sets of ten texture pairs (S_1 and S_2). For each set, we choose one representative texture per class (pigments on canvas, paint, paper, hatching, cross-hatching, dots, near-regular or irregular patterns, noise and grid).

To construct S_1 and S_2, each of the original textures is transformed using a 2D static version of the fractalization algorithm proposed by Bénard et al. [2009]. Here, three scales of the texture are alpha-blended (with the coefficients $1/3, 1/2$ and $1/6$). This number is a minimum to ensure temporal continuity in most dynamic scenes. Figure 1 shows the twenty pairs – original and transformed version – obtained for the two series.

3.2 Procedure

We realize the ranking experiment via a dynamic web interface to enrich and diversify our panel of subjects. Nevertheless, in order to keep a certain amount of control on the participants' origin, we have restricted the diffusion of this web site to known people. We are aware that our interface prevents us from having a precise control on the experimental conditions (screen resolution, calibration, viewing angle and ambient lightning). Consequently, we paid special attention to assessing the statistical validity of the resulting data as detailed in Section 4.1. We consider this trade-off admissible with regard to the number of participants and the diversity of their skills in computer graphics (naive: 58%, amateur or professional infographists: 8.5%, researchers: 22.4% and unknown: 11.1%).

[1]The user study is fully available at: http://artis.inrialpes.fr/~Pierre.Benard/TextureQualityMetric with full scale images of the two series.

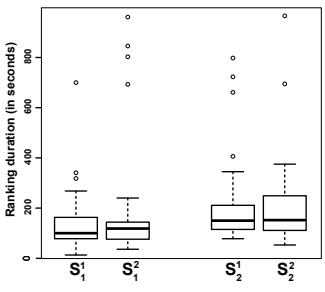
On each trial, after presenting the general context of this study, the subject is asked to place the pairs in order from the lowest to highest by perceived distortion. This ordering can be partial if texture pairs seem identically distorted. After the ranking of the second set, the subject is asked to specify for each of these last ten pairs the criteria she thought to have used. We provide three basic criteria: *contrast*, *sharpness* and *scale*; but we also allow the user to freely type personal criteria. The two image sets are shown randomly at each user trial to avoid learning effects. The duration of each task (first ranking, second ranking and criteria specification) are recorded.

4 Statistical Analysis

103 people took part in this study. Among them, 45 started with the first image set (S_1^1 then S_2^2) and 58 with the second (S_2^1 then S_1^2).The statistical analysis of the resulting two datasets are carried out identically in three steps. After studying the potential learning effect, we propose to derive an interval scale of relative perceived distortion intensity. Finally we run an analysis of the criteria used during the ranking.

4.1 Ranking Duration and Concordance

First, we estimate whether the presentation order of the two image sets has an influence on the final ranking to verify that the subjects are not biased by the first ranking while doing the second. The inset shows the boxplot of the experiments duration for the two series depending



on presentation order. Notice that for each series the distribution of durations is similar whatever the presentation order. Thus, we can conclude that the presentation order has no significant influence on the subjects' attention. Moreover the mean duration of both series is comparable (211s and 147s respectively).

In order to quantify the consistency of rankings provided by the users panel, we compute the Kendall's coefficient of concordance (Kendall's W) [Kendall 1975] over the four results sets S_i^j and the S_i obtained by merging the previous series. This non-parametric measurement is commonly used to evaluate the agreement among raters (between 0 for no-agreement and 1 for and 1 full-agreement) without the need to assume any specific distribution.

	S_i^1	S_i^2	S_i
$i=1$	0.598	0.55	0.574
$i=2$	0.576	0.657	0.599

As shown in the inset table, the coefficients of concordance of the merged results sets S_i remain comparable with the un-merged ones. Regarding these statistics the analysis of merged data seems relevant.

To validate the statistical significance of Kendall's W we perform a χ^2 test with the null hypothesis H_0 that there is no agreement among the subjects. In the six cases, this hypothesis may be rejected at $\alpha = 0.001$ level for 9 degrees of freedom. Hence, we can conclude that there is some agreement amongst the participants, that is, the rankings are not effectively random.

4.2 Interval Scale of Relative Perceived Distortion

An ordinal scale can be directly derived by tabulating the raw data to show how often each pair was placed in each rank position (frequency) and calculating their mean ranks. However, it gives no quantification of perceived differences between texture pairs: it doesn't inform on *how much* higher one pair is distorted compared to another. By assuming a normal distribution of the data[2] and using the Thurstone's *law of comparative judgment* [Torgerson 1958], we can convert the proportion of each pair (frequencies divided by number of trials) into z-Score (Figure 1b). These z-Scores correspond to relative differences in perceived distortion between texture pairs on a perceptually-linear scale. For both image sets (Figure 1a), note that the unstructured textures (noise, pigment, paper) seem to be more robust to the *fractalization* process. On the contrary, textures exhibiting more distinctive features are in both cases judged as the most severely distorted.

In order to go a step further, we perform statistical hypothesis tests to ensure that the perceived similar distortion intensity is significant. We use the non-parametric *Wilcoxon rank sum test* (also called *MannWhitney U test*) for assessing whether two independent samples of observations come from the same distribution. The *U test* has both the advantages of working on ordinal data and of being more robust towards outliers than the *Student t-test*. The null hypothesis H_0 is that the two considered samples are drawn from a single population, and therefore that their distribution is equal. In our case, this test has to be run for each pair of samples: $(\text{tex}_{i,m}, \text{tex}_{i,n})$ where $1 \leq m \leq n \leq 10$ (i.e. ninety times).

In Figure 1, we frame groups of pairs for which the null hypothesis cannot be rejected. By looking at the corresponding texture pairs, we observe that the overall contrast of patterns seems to be the most significant criterion. In comparison, feature shapes seem to play a less important role in this grouping.

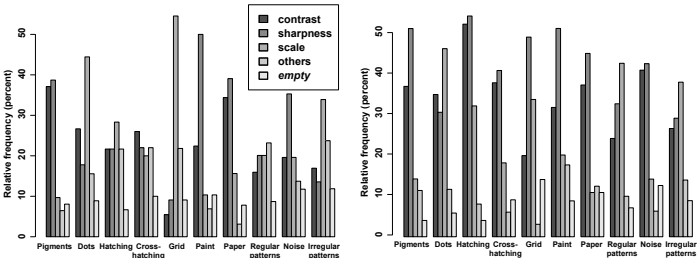
[2]Empirically verified using a Q-Q plot and a *Shapiro-Wilk test*: the null hypothesis of normally distributed data cannot be rejected.

Note that the interval scales and groups of each image set are not fully identical. It indicates that the classes of media we defined *a priori* only partially fit the classification based on the distortion. In particular, the two representative textures of the "grid" and "cross-hatching" classes are judged distorted differently. We think that this is due to their strong difference in terms of contrast, pattern density or feature shapes.

4.3 Ranking Criteria

We finally analyze the criteria that each subject considered she used during the ranking. Figure 2c shows the relative frequency at which the three proposed criteria have been used per series. Overall, they are quite similar, with a little preference for *sharpness* and then *contrast* in S_2. However when we consider this distribution of criteria for each texture pair (Figures 2a and 2b), we observe irregular preferences for different criteria. We thus conjecture that the content of each texture class triggers different criteria when assessing the similarity between original and transformed textures.

The analysis of the additional criteria proposed by the participants also shows that the notions of *density* (15% of these criteria), *shape* (10%) and *pattern coherence* (21%) and to a lesser extent *frequency* (4%) and *relief* (2%) are relevant as well.



(a) *First texture pairs set.* **(b)** *Second texture pairs set.*

	contrast	sharpness	scale	other	*empty*
S_1	21.96%	26.86%	24.83%	17.40%	8.95%
S_2	28.27%	35.21%	21.72%	7.12%	7.07%

(c) *Frequencies for each series.*

Figure 2: *Relative frequency at which the criteria have been used: For each texture pair (a,b) and for each series (c).*

5 Correlation with Objective Metrics

In a second step, we review a large range of image metrics and statistics, with the hope of correlating them with the two previously derived subjective scales. We use the *Pearson product-moment correlation coefficient* r and linear regression to evaluate this correlation.

5.1 Image Quality Metrics

We first examine eleven well-known objective quality assessment metrics (implemented by Matthew Gaubatz in the MeTriX MuX Matlab© package[3]): the peak signal-to-noise ratio, the signal-to-noise ratio, the structural similarity (SSIM) index and multi-scale SSIM index, the visual signal-to-noise ratio , the visual information fidelity (VIF) and pixel-based VIF, the information fidelity criterion and the universal quality index.

[3]Available at: http://foulard.ece.cornell.edu/gaubatz/metrix_mux/

None of these metrics shows a significant correlation with the subjective interval scales. This conclusion was predictable as these metrics have been designed to assess the quality of images suffering limited amount of distortion (noise, blur, compressions artifacts, etc). In comparison, the *fractalization* process may strongly modify the appearance of the distorted texture.

5.2 Global and Local Image Statistics

Because the three criteria – *contrast*, *sharpness* and *scale* – have to be considered simultaneously, we cannot expect global image statistics to give significant results, especially when one considers that our textures are not "natural images". Our experiments on histograms, power spectra and distribution of contrast measurements [Balboa and Grzywacz 1993] are, as expected, inconclusive.

Taking inspiration from the field of texture analysis [Tuceryan and Jain 1993], we choose a statistical method – the *gray level co-occurrence* (GLC) model – which estimates local image properties related to second-order statistics (like variance, standard deviation and correlation). Moreover, psychophysical experiments have shown that the GLC model matches certain levels of human perception [Julesz et al. 1976] and it has been successfully used and perceptually validated for texture synthesis [Copeland et al. 2001]. Finally, this model might be related to the *density* and *pattern coherence* criteria freely proposed by the subjects.

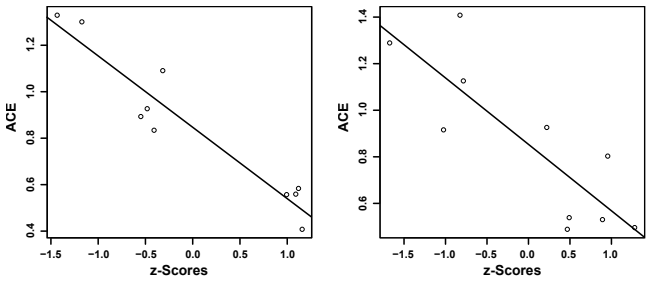


Figure 3: *Linear regression of ACE against z-Scores for S_1 (left) and S_2 (right).*

We measure the distortion between original and distorted textures by computing their GLC matrices and then the distance between these two sets of matrices with the *average co-occurrence error* (ACE) of Copeland et al. This error metric is highly correlated with the perceptual interval scales for both series. We obtain the maximum absolute Pearson's correlations of 0.953 for S_1 and 0.836 for S_2 (with, respectively, a *p-value* < 0.0001 and 0.003 for 8 degrees of freedom) considering the GLC matrices for all displacements up to $\mathcal{T}_{NX} = \mathcal{T}_{NY} = 4$ pixels with a $G = 32$ gray levels quantization (with the notation of Copeland et al.).

Figure 3 shows the corresponding linear regression of the ACE against z-Scores for both series ($r^2 = 0.9075$ and 0.6992 respectively, with the same *p-values* as for Pearson's correlations). This high correlation for both image sets confirms that the ranking differences observed in Section 4.2 are coherent and that an *a priori* classification is not a suitable predictor of the distortion.

6 Conclusions

In this work, we proposed the *average co-occurrence error* as a meaningful quality assessment metric for *fractalized* NPR textures. We validated the relevance of this predictor by showing its strong correlation with the results of a user-based ranking experiment.

We plan to investigate potentially better suited texture and vision descriptors to derive an improved objective quality metric. Image retrieval approaches, based on extracted texture features, seem a promising field of inspiration. Longer term future work will consider the dynamic version of the *fractalization* process. In this case, the methodology we developed for the current study will have also to consider the trade-off between temporal continuity and texture dissimilarity to the original medium.

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