Colour Fractal Analysis for Video Quality Assessment

Mihai IVANOVICI; MIV Imaging Venture Laboratory, Department of Electronics and Computers, Faculty of Electrical Engineering and Computer Science, "Transilvania" University; Braşov, România

Noël RICHARD and Christine Fernandez-Maloigne; XLIM-SIC UMR CNRS 6172, Signals, Images and Communications, University of Poitiers; Poitiers, France

Abstract

Fractal dimension and lacunarity are two fractal measures widely used for image analysis, segmentation and indexation. In this paper, we show how these two fractal features are able to capture several aspects that characterize the degradation of the video signal, based on the fact that the quality perceived is directly proportional to the fractal complexity of an image. Thus, we demonstrate that the fractal dimension and lacunarity can be used to objectively assess the quality of the video signal and how they can be used as metrics for the user-perceived video quality degradation for an MPEG-4 streaming application.

Unfortunately, all the existing approaches are defined only for binary and grey-scale images. Based on the probabilistic algorithm for the estimation of the fractal dimension and computation of lacunarity, we propose a colour approach that makes possible the analysis of the complexity in the RGB colour space of any colour image. We discuss our experimental results and then draw the conclusions.

Quality Degradation Metrics for Video Signal

There exist many quality measures or criteria for video and image analysis. First of them are based on simple fidelity metrics, like signal to noise ratio. During the last decade, several quality measures, both subjective and objective, have been proposed, especially for the assessment of the image compression, image rendering on screen or digital cinema. Most of them use models of the human visual system to express the image perception as a specific pass band filter (to be more precise, a pass band filter for the achromatic vision and a low pass filter for the chromatic one). In this article we explore a well-known property of the human visual system, i.e. to be "sensitive" to the visual complexity of the image. We use fractal features - thus a multiscale approach - to estimate this complexity.

For the quantification of the quality of a video sequence, there are two types of metrics: subjective and objective. They can also be: (i) *reference-based*, when the both the video sequence at the transmitter and the video sequence at the receiver are available, then the sequence at receiver is compared to the original sequence at transmitter, and (ii) *without reference* or *no reference*, when the video sequence at the transmitter is not available, therefore only the video sequence at the receiver is being analyzed.

The subjective video quality measurements are time consuming and must meet complex requirements (see the ITU-T recommendations [3], [20], [9], [10]) regarding the conditions of the experiments, such as viewing distance and room lighting. The objective metrics are usually preferred, because they can be implemented as algorithms and are human-error free. The most complex are based on models of the human-vision system, but some are simply distance measures, such as the Root Mean Square Error (RMSE) or the Peak Signal-to-Noise Ratio (PSNR). These simple measures are unable to capture the degradation of the video signal from a user perspective.

For the quantification of the user-perceived degradation, image attributes like sharpness and colorfulness are used in [31, 30, 32]. The Video Quality Experts Group (VQEG)[1] is the main organization concerned by the the perceptual quality of the video signal and they reported on the existing metrics and measurement algorithms [7]. A survey of video-quality metrics based on models of the human vision system can be found in [28] and several no-reference blockiness metrics are studied and compared in [24]. OPTICOM[2] is the author of one of the latest metric for video quality evaluation called "Perceptual Evaluation of Video Quality" (PEVQ). This reference-based metric is used to measure the quality degradation in case of any video application running in mobile or IP-based networks. The PEVQ Analyzer [19] measures several parameters in order to characterize the degradation: brightness, contrast, PSNR, jerkiness, blur, blockiness etc.

Most of the existing metrics for the video quality are used to quantify the degradation introduced by the compression algorithm itself, as a consequence of the reduced bit rate. We are interested in objectively assess the degradation in video quality caused by the packet loss at network level [16].

In our experiments, we identified two kinds of degradation: (i) the degradation that affects the sequence, i.e. the temporal component of the signal and (ii) the degradation that affects the frames, i.e. the spatial component. Given the way the majority of the video frames are degraded (see Figure), the most useful metric would be the blockiness, which objectively quantifies the impairments. To quantify the degradation of a single video frame, one could simply measure the affected area in number of pixels of number of 8x8 blocks or an appropriate perceptual metric, able to quantify the degradation from a human perspective. Apart from blockiness, the degraded frames are "dirty", i.e. many blocks containing other information than they should, instead of a clean frame with one football player on a green grass background. Therefore a metric able to quantify the *dirtiness* would be useful.

The degradation that affects the video frames is in fact a mixture of several impairments, inclusing blockiness and the appearence of new colours. The modifications of the image content reflect both in the colour histograms and the spectral representation of the luminance and chrominances (high frequences due to blockiness). Given all above, we consider that metrics like blur, contrast, brightness, even blockiness lose their meaning and they are not able to reflect the degradation, therefore they cannot be applied for such degraded video frames. Metrics able to capture all the aspects of the degradation that reflect the colour spread, as well the amount of new colours occurring in the degraded video frames would be more appropriate. Given all the above

[1] http://www.vqeg.org

[2] http://www.opticom.de

considerations, the approaches based on on multiscale analysis and image complexity are more adapted to the video quality assessment. Fractal analysis-based approaches is just an example of such methods.

Fractal Analysis

The fractal geometry was introduced by B. Mandelbrot in 1983 to describe self-similar sets called fractals [17]. It is also used to characterize natural objects that are impossible to describe by using the classical geometry. Fractal dimension and lacunarity are the most known and used fractal measures. The fractal dimension is a measure that characterizes the complexity of a fractal set, indicating how much space is filled, while the lacunarity is a mass distribution function indicating how the space is occupied [27]. These two fractal properties are succesfully used to discriminate between different structures exhibiting a fractal-like appearence [4, 12, 6], for classification and segmentation, due to their invariance to scale, rotation or translation. The fractal geometry proved to be of a great interest for the digital image processing and analysis in an extremely wide area of applications, like finance [22], medicine [26, 12, 1] and art [25].

There exist several different mathematical expressions for the fractal dimension, but the box-counting is the most popular due to the simplest algorithmic formulation, compared to the original Hausdorff definition [5]. The box-counting definition of the fractal dimension is $D_{box} = -\frac{logN_\delta}{log\delta}$, where $N(\delta)$ is the number of boxes of size δ needed to completely cover the fractal set. The first practical approach belongs to Mandelbrot, but that was followed by the the elegant probability measure of Voss [29, 11]. On a parallel research path, Allain and Cloitre [2] and Plotnick [23] developed their approach as a version of the basic box-counting algorim. All the other approaches for the computation of the fractal dimension, like δ-parallel body method[3] [18] or fuzzy [21] are more complex from a point of view of implementation and more difficult to extend to a colour multi-dimensional space. On the other hand, despite the large number of algorithmic approaches for the computation of the fractal dimension and lacunarity, only few of them offer the theoretical background that links them to the Hausdorff dimension.

However, such tools were developed long time ago for grey-scale small-size images, but now the acquisition techniques evolved (therefore the spatial resolution and quantification have changed) and the world of images became coloured. The very few existing approaches for the computation of fractal measures for colour images are restricted to a marginal colour analysis and transform a grey scale problem in false colour [1]. In this paper, we briefly present our colour extension of the existing probabilisting algorithm by Voss [29], fully described in [14]. Then we show how the colour fractal dimension and lacunarity can be used to characterize the degradation of the video signal for an MPEG-4 video streaming appplication. We discuss our experimental results and then draw the conclusions.

Colour Fractal Dimension and Lacunarity

The probabilistic algorithm defined by Voss [29] upon the proposal from Mandelbrot [17] considers the image a set of points S in an Euclidian space of dimension E. The spatial arrangement of the set is characterized by the probability matrix $P(m,\delta)$, the probability of having m points inside a cube of size δ (called *box*), centered in an arbitrary point of S. The matrix is normalized so that $\sum_{m=1}^{N} P(m,\delta) = 1$, $\forall\delta \in R^+$, where N is the number of pixels included in a box of size δ. Given the total number of points in the image is M, the number of boxes that contain m points is $(M/m)P(m,\delta)$. The total number of boxes needed to cover the image is:

$$\langle N(\delta)\rangle = \sum_{m=1}^{N} \frac{M}{m} P(m,\delta) = M \sum_{m=1}^{N} \frac{1}{m} P(m,\delta) \tag{1}$$

Consequently $N(\delta) = \sum_{m=1}^{N} \frac{1}{m} P(m,\delta)$ is proportional to L^{-D}, where D is the fractal dimension to be estimated.

A grey-level image is a discrete surface $z = f(x,y)$ where z is the luminance in every (x,y) point of the space. A colour image is a hyper-surface in a colour space, e.g. RGB, therefore we deal with a 5-dimensional Euclidian hyper-space and each pixel is a 5-dimensional vector. The classical algorithm of Voss uses boxes of variable size δ centered in the each pixel of the image and counts the number of pixels that fall inside that box. We generalize this by counting the pixels for which the Minkowski infinity norm distance to the center of the hyper-cube is smaller than δ. Practically, for a certain square of size δ in the (x,y) plane, we count the number of pixels that fall inside a 3-dimensional RGB cube of size δ, centered in the current pixel. The theoretical development and validation on synthetic colour fractal images can be found in [14].

Even from the very beginning, when Mandelbrot introduced the fractal geometry, he was aware by the fact that the fractal dimension itself is not sufficient to fully capture the complexity of non deterministic objects. He defined and used the lacunarity as a complementary metric. Later on, Voss expressed it based on the probabilities $P(m,\delta)$ and using the first and second order moments of the measure distribution (2). Following the previous considerations, the lacunarity can be therefore computed for colour images as well.

$$\Lambda(\delta) = \frac{M^2(\delta) - (M(\delta))^2}{(M(\delta))^2} \tag{2}$$

$$M(\delta) = \sum_{m=1}^{N} mP(m,\delta) \tag{3}$$

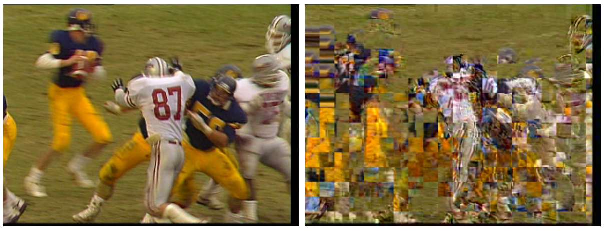
$$M^2(\delta) = \sum_{m=1}^{N} m^2 \cdot P(m,\delta) \tag{4}$$

The lacunarity is linked to the topological organisation of objects in an image, being a scale-dependent measure of spatial heterogeneity. Images with small lacunarity are more homogeneous with respect to the size distribution and spatial arrangement of gaps. On the other hand, images with larger lacunarity are more heterogeneous. In addition, lacunarity must be taken into consideration after inspecting the fractal dimension: in a similar manner with the Hue-Saturation couple in colour image analysis, the lacunarity becomes of greater importance when complexity, i.e. the fractal dimension, increases.

Approach Argumentation and Validation

In Figure 1 we present two video frames: one from the original video sequence and the corresponding degraded video frames from the sequence at the receiver. The computed colour fractal dimensions are 3.14 and 3.31, respectively. One can see that the larger fractal dimension reflects the increased complexity of the degrated video frame. The increased complexity comes from the blockiness effect, as well as from the dirtiness and augmented colour content (see also the 3D histograms in Figure 3).

[3] also called covering-blanket approach, Minkowsky sausage or morphological covers.



(a) original video frame, FD=3.14 (b) degraded video frame, FD=3.31

Figure 1. Two video frames from the "football" video sequence.

The corresponding lacunarity curves are depicted in Figure 2. One can see that the curve for image (b) is placed higher than the curve for (a) indicating a more lacunar and heterogeneous image. The complexity revealed by the lacunarity curves is in accordance with the fractal dimension: the orignal unaffected video frame being a less lacunar image than the degraded one.

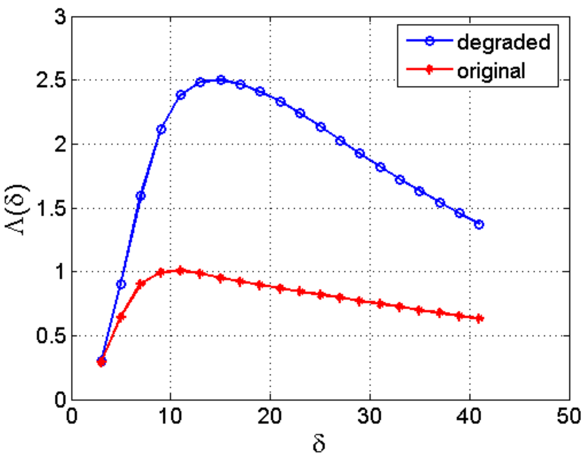
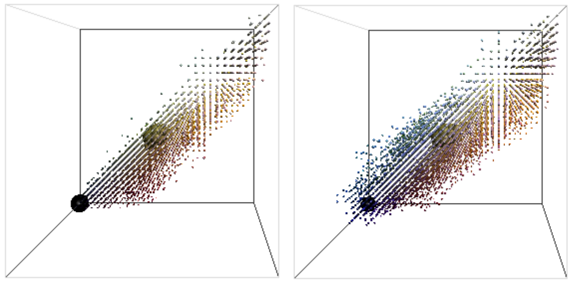


Figure 2. Lacunarity curves for the images in Figure 1.

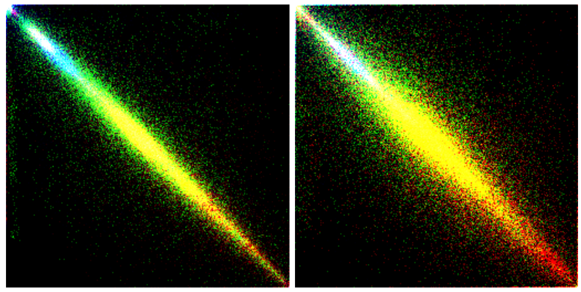
Given the lacunarity is a measure of how the space is occupied, we present in Figure 3 the 3D histograms in the RGB colour space, as a visual justification. One can see that the histogram of the degraded video frame is more spreaded than the one of the original video frame, indicating a more rich image from the point of view of its colour content.

In order to quantify the spread of the 3D histograms, we computed the co-occurence matrices for the two video frames. Another reason for doing this is the fact that in the case of a random fractal the fractal dimension is proportional to the variance of the increments [29]. Therefore, we computed the co-occurence matrices for a neighbourhood distance of one pixel, on the horizontal direction. In this way the computed co-occurence is a measure of the correlation between pixels. In Figure 4, for the two video frames we show the three overlayed co-occurence matrices, one for each RGB component. The results indicate that the variance of the values is larger for the degraded video frames, indicating a smaller correlation between the neighbour pixels. The lack of correlation is the natural consequence of the sum of impairments that affect the degraded frame. As shown in [13], that the co-occurrence matrix shape is linked to the fractal dimension of the signal or image. So these two results for 3D histograms and co-occurence are a first validity proof for a fractal approach.



(a) original video frame (b) degraded video frame

Figure 3. The 3D histograms for the two video frames.



(a) original video frame (b) degraded video frame

Figure 4. The overlayed co-ocurrence matrices.

To be complete, we analyze the video frames from the point of view of their spectral fluctuations. Random function complexity can be defined on its power density spectrum. For a fractal signal $v(t)$, the power density function varies upon a power law in $\frac{1}{f^{\beta}}$. So the Fourier transform $V(f,T)$ computed on T time samples of $v(t)$ allow to express the spectral density function $S_V(f)$ as:

$$S_V(f) \propto T|V(f,T)|^2 \text{ as } T \to \infty \tag{5}$$

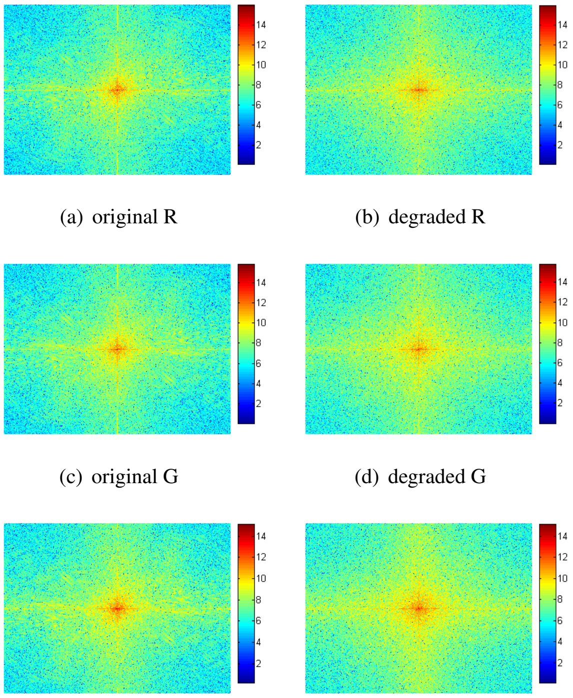
The link between the power law of β and the fractal dimension D is defined by the relation [29], where E is the size of the euclidian space ($E = 1$ for a 1D signal).

$$D = E + 1 - H = E + \frac{3-\beta}{2} \tag{6}$$

Given that it is almost impossible to estimate the impact of the artifacts in the spatial domain, without any reference (original video signal), in the frequence domain is clearly enough that the artifacts induce very high frequencies and a specific modification of the spectrum which could be close to a complexity induced by a fractal model.

In Figure 5 we show the 2D FFT of the two video frames, for each colour plane, and in Figures 6, 7 and 8 the horizontal and vertical slices of the spectra, corresponding to the spatial frequencies $v = 0$ and $u = 0$, respectively.

In a first comment, we clearly express that the marginal analysis (plane by plane) doesn't reflect the entire colour degradation that affects the video signal. Thus as we prove, the degradations induces a complexity fluctuation that is well intercepted by the fractal dimension. So it's a new proof that justify the use of a colour estimation of degradation by colour fractal approaches.

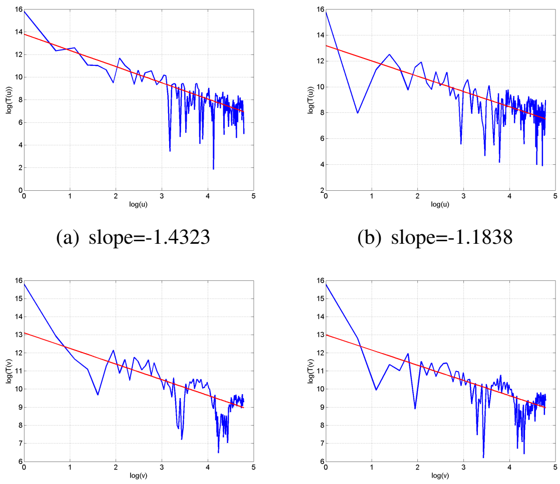


(a) original R (b) degraded R

(c) original G (d) degraded G

(e) original B (f) degraded B

Figure 5. *2D FFT of the two video frames, per plane.*



(a) slope=-1.4323 (b) slope=-1.1838

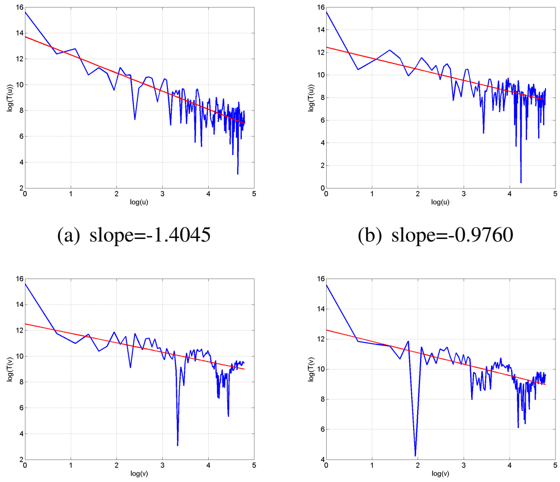
(c) slope=-0.8642 (d) slope=-0.8410

Figure 6. *T(u) (top) and T(v) (bottom) for the Red plane, for the original (left) and degraded (right) video frames.*

In addition, due to the complexity, to the colour Fourier transform based on Quaternionic approaches, our approach is the more suitable at this moment for real time implementation. For an image of size N^2, the complexity of a parallel implementation of our approach would be $O(N^2)$, while for a 2D Fast Fourier Transform the best case is of $O(N^2 logN)$ complexity.

Experimental results

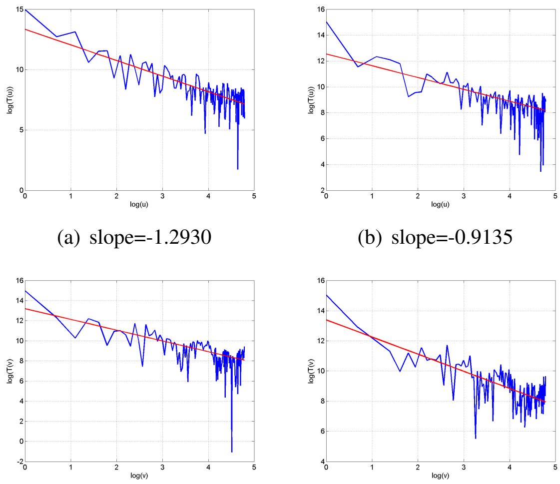
From the plethora of IP-based video application, we chose an MPEG-4 streaming application. Streaming applications usually use RTP (Real-Time Protocol) over UDP, therefore the traffic



(a) slope=-1.4045 (b) slope=-0.9760

(c) slope=-0.7330 (d) slope=-0.7560

Figure 7. *T(u) (top) and T(v) (bottom) for the Green plane, for the original (left) and degraded (right) video frames.*



(a) slope=-1.2930 (b) slope=-0.9135

(c) slope=-1.0709 (d) slope=-1.1370

Figure 8. *T(u) (top) and T(v) (bottom) for the Blue plane, for the original (left) and degraded (right) video frames.*

generated by such an application is inelastic and doesn't adapt to the network conditions. In addition, neither UDP itself or the video streaming application implement a retransmission mechanism. Therefore, the video streaming applications are very sensitive to packet loss: any lost packet in the network will cause missing bits of information in the MPEG video stream.

Given that packet loss is the major issue for an MPEG-4 video streaming application, in our experiments the induced packet loss percentage varied from 0 to 1.3%. Above this threshold, the application cannot longer function (i.e. the connection established between the client and the server breaks) and tests cannot be performed. The test setup is depicted in Figure 9: the MPEG-4 streaming server we used was the Helix streaming server from Real Networks[4] and the MPEG-4 client was `mpeg4ip`[5]. We modified the source code of the client to record the received video sequence as individual frames in bitmap for-

[4] http://www.realnetworks.com
[5] http://mpeg4ip.sourceforge.net

mat. We ran the tests using three widely used video sequences: "football", "female" and "train", MPEG-4 coded. More results and details about the experimental setup are to be found in [8, 15].

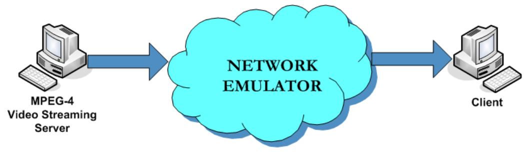


Figure 9. *The test setup.*

In Figure 10 one may see three type of degradation that occurs in our tests: *important* or *severe* degradation (top); *less-affected* frames (middle) and *special* or green degraded frames (bottom). The difference ΔFD between the degraded and the original corresponding video frame will be considerable for the first two images that exhibit an important degradation - i.e almost the entire image is affected by severe blockiness, and the scene cannot be understood. ΔFD will be small, but still positive for less affected images (the football players may no longer be identifiable, but the rest of the scene is unchanged). For the "green" images the colour fractal dimension is smaller than the one of the corresponding original frames, therefore the ΔFD will be negative.

The corresponding lacunarity curves are depicted in Figure 11. The largest lacunarity is for the most affected video frames, as expected. From a human perception point of view, the colour lacunarity curves are able to reveal the correct ranking, as well as the colour fractal dimension.

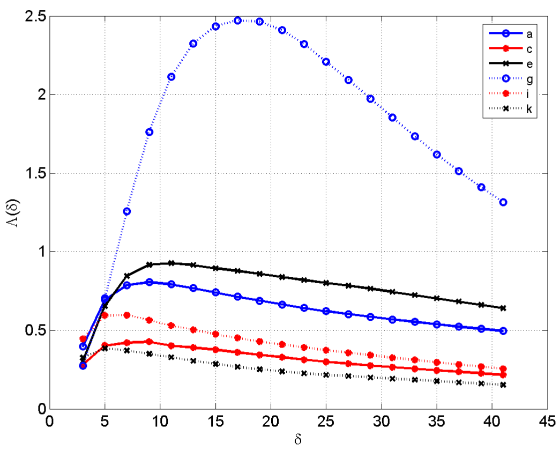


Figure 11. *Lacunarity curves for the images in Figure .*

In order to analyse the degradation in time, in Figure 12 the evolution of the colour fractal dimension in time is depicted. One can see that the original "football" sequence is characterized by a large variation in the complexity of the image, due to the fact that the scene changes and also due to the high dynamicity. Therefore the variation of the colour fractal dimension due to degradation is almost insignificant. In addition, due to the lost video frames, the two curves will get more and more desynchronized in time, which makes the analysis more difficult. However, it is possible to create a reference-based metric by using the colour fractal dimension (note the grey zones that indicate a slight increase of the fractal dimension due to quality degradation).

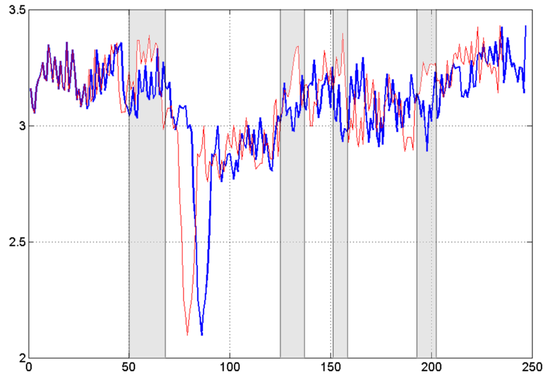
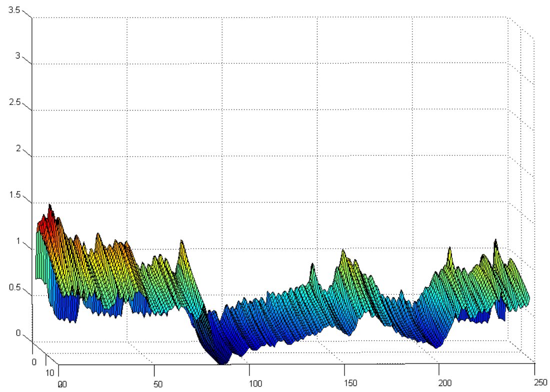
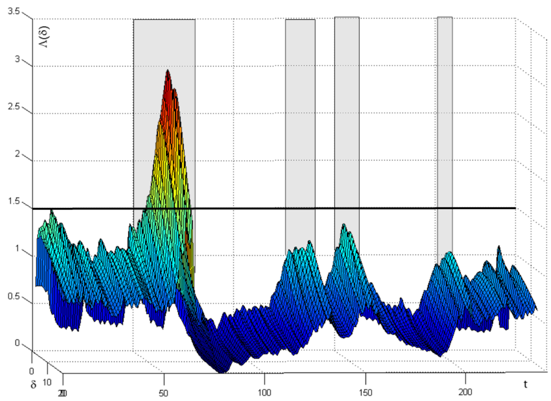


Figure 12. *The fractal dimension as a function of time, blue-original, red-received, for the "football" video sequence.*



(a) original video seq



(b) degraded video seq

Figure 13. *The lacunarity curves versus time for the "football" sequence.*

One can note that for the original "football" video sequence the colour lacunarity has also an important variation (see Figure 13) from frame to frame, but its values are comprised between 0 and 1.5. For the degraded video sequence (b) we can see that the lacunarity skyrockets up to 3.0 for the interval of video frames affected by important degradation (the first interval market with grey). The less imporant degradation (the next greyed intervals) can only be detected if we take as reference the lacunarity of the original video sequence. In order to implement a no-reference metric, $lacunarity \geq 1.5$ can indicate the severe degradation.

We analyzed two more video sequences: "female" and "train" (Figure 14). The corresponding colour fractal dimension as a function of time are depicted in Figure 15. The lacunarity


(a) frame 70, FD=3.038


(b) frame 93, FD=2.995


(g) FD=3.357, $\Delta FD = 0.319$


(h) FD=3.373, $\Delta FD = 0.378$


(c) frame 120, FD=2.804


(d) frame 157, FD=2.975


(i) FD=2.983, $\Delta FD = 0.178$


(j) FD=3.179, $\Delta FD = 0.205$


(e) frame 22, FD=3.216


(f) frame 24, FD=3.158


(k) FD=2.284, $\Delta FD = -0.932$


(l) FD=2.464, $\Delta FD = -0.694$

Figure 10. *Video frames from the “football” sequence, both original (a-f) and degraded (g-l), exhibiting different levels of degradation.*


(a) frame 23

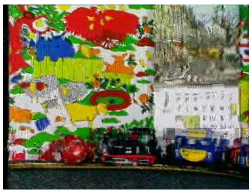

(b) frame 24


(e) frame 0


(f) frame 77


(c) frame 42


(d) frame 185


(g) frame 105

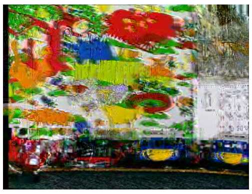
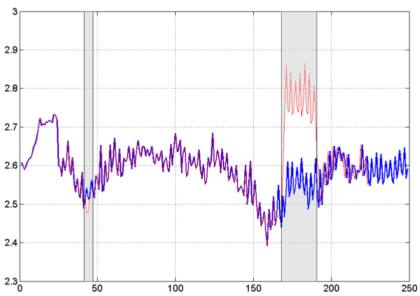
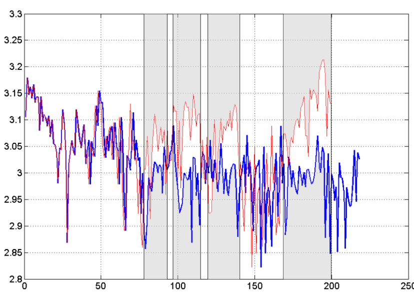

(h) frame 192

Figure 14. *Frames from “female” (a-d) and “train” (e-h) video sequence.*

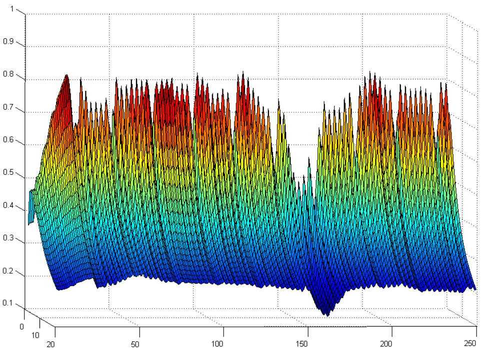


(a) “female”

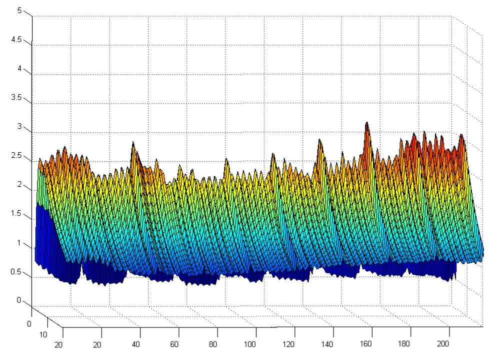


(b) “train”

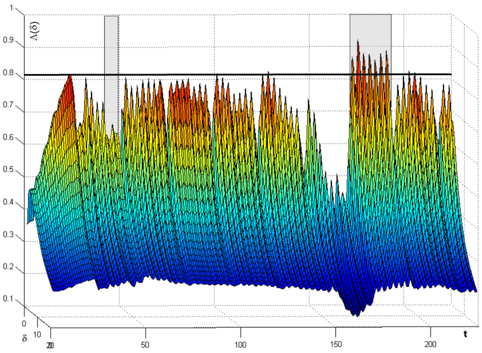
Figure 15. *The fractal dimension as a function of time (blue-original, red-received / degraded) for the “female” and “train” video seq.*



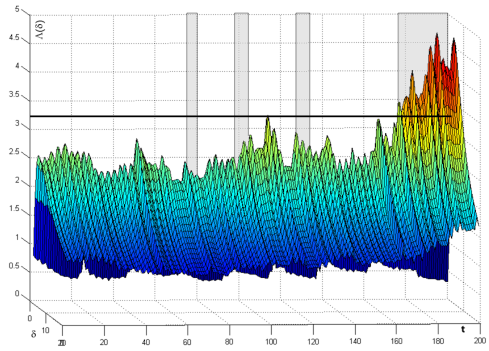
(a) original video seq



(c) original video seq



(b) degraded video seq



(d) degraded video seq

Figure 16. *The lacunarity curves versus time, for "female" and "train".*

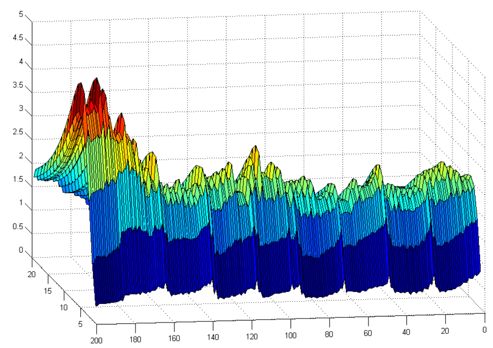


Figure 17. *Periodicity of the lacunarity in time for the "train" video sequence.*

curves are presented in Figure 16.

For the "female" and the "train" video sequences one may note that the lacunarity curves exhibit a certain periodicity in time (e.g. see Figure 17). The explanation is the fact that from time to time the video signal is affected by a not-so-severe blockiness due to the encoding mechanisms only. This is not visible on the "train" video sequence, due to the high complex content of the image, but it can be easily seen on the "female" video sequence - an example is depicted in Figure 14 b).

Conclusions

In this paper we show how the colour fractal dimension and lacunarity can be used to characterize and objectively assess the degradation of the video signal. For the computation of the two metrics we propose a colour extension of the classical probabilistic algorithm designed by Voss. We demonstrated that our approach is able to capture the relative complexity of the video frames and the sum of aspects that characterize the degradation. To support our results and conclusion, we also investigated the 3D histograms and the co-occurrence matrices of the two video frames. In addition, the fractal features are well correlated to the perceived complexity by the human vision system, thus they are of great interest as objective tools in a video quality analysis tool set.

We conclude that the colour lacunarity itself can be used as no-reference metric to detect the important degradation of the video signal at the receiver. The colour fractal dimension and lacunarity can be definitely used as a reference-based metrics, but this is usually impossible in a real environment setup. The colour fractal dimension is not enough to be used as stand-alone metric but in a reference-based scenario it can serve for the assessment of the quality degradation.

Our choice of using the RGB colour space perfectly suits the probabilistic approach, and the extension from cubes to hypecubes was natural and intuitive. We are aware of the fact that the RGB colour space may not be the best choice when designing an image analysis algorithm from the point of view of the human vision system. Given that a perceptual objective metric is desired, we plan to further develop our colour fractal metrics by using other colour spaces, e.g. Lab or HSL, capable of capturing and reflecting the human perception of colours.

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Author Biography

Mihai Ivanovici received his B.Sc. from the Transilvania University, Braşov, România (2001), then his M.Sc. (2002) and Ph.D. (2006) from the Politehnica University, Bucureşti, România. His research interest include colour fractal analysis and mathematical morphology with application in medicine. Currently, he is a lecturer within the Department of Electronics and Computers, Transilvania University, Braşov, România and head of MIV Imaging Venture Laboratory.

Noël Richard received the M.Sc and Ph.D. from the University of Poitiers, France in 1988 and 1993 respectively. Since 1992, he is a researcher at XLIM-SIC (Signals, Images and Communications) UMR CNRS 6172 laboratory and associate professor at University of Poitiers, France. His research interests include colour perception and image analysis by means of fractal geometry, colour and texture features.

Christine Fernandez-Maloigne is a full professor and she manages a joint research unit between CNRS and University of Poitiers (France) since 2008. Her scientific interests include image and video coding, indexing, watermarking and image quality assessment. She is an expert in numerous French research organisms and for the European Commission. She represents France in the Division 8 (Image Technology) of CIE and she is also member of the French National Body for the ISO JPEG.