Fractal-based Impressionist Style Rendering

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***Abstract*—We propose a novel image processing model that produces impressionist style paintings from photographs. Characteristics, here called impressionist constraints, are extracted from photographs and expressed as heightmap data. We use a constrained fractal model to generate a new image that satisfies the initial heightmap data constraints. Then, we enhance the characteristics extraction model and present the new resulting images. Other results are presented and illustrate the ability of our model to produce impressionist effects on a large variety of photographs.**

***Keywords*-non photorealistic rendering; painterly rendering; impressionism; fractals;**

I. INTRODUCTION

Historically, the Renaissance painters had developed new techniques to provide realism in the visual arts. The development of highly realistic linear perspective, the studies of lighting (light and shadows) have been widely depicted in most paintings. During this period artists tried to produce photorealist paintings and consequently brush strokes were invisible. With the impressionist art of painting, new considerations have been studied and the aim became to capture the momentary. As mentioned by Atencia et al. [1] impressionist paintings are characterized by visible brush strokes, open composition, emphasis on light and color arrangement. Impressionist painters strove to capture the momentary and their painting process can be described as a set of brush strokes that preserve overall visual effects instead of details. Thus, this construction can be considered as a set of preserved *impressionist constraints* combined with an *impressionist filling process*.

In this paper, we present a novel image processing model that produces impressionist style renderings. Starting with an image, usually a color photograph, we extract its characteristics as a set of surface constraints to be preserved. Thus, as an image can be decomposed into several component layers and in several color systems, we potentially have many surfaces to process. At this stage, we propose to produce a new image by generating new image surfaces (*i.e.* component layers) according to the fixed constraints. For this part, we adopt a fractal-based model capable of making controllable fractal surfaces that matches some predefined positions. Our choice is mainly motivated by the capability of the model to preserve constraints and create easily controllable smooth perturbations reproducing the scheme of *impressionist constraints* and *impressionist filling* process. Moreover, existence of connections between painting art — specially expressionism and *Les Automatistes* — and fractal science images[2] or between fractal and impressionism [3] have already been proposed and, more particularly, many studies [4], [5], [2], [6] suggest that Pollock's drip paintings present fractal characteristics.

Thus, in the next sections, we present previous work, our model workflow, methods used to extract photograph characteristics, then enhance the data extraction model and present our results.

II. RELATED WORK

Simulating artistic media, and particularly painting, is one of most important topics in non-photorealistic rendering. Digital painting strategies can be classified in two main categories: physical-based simulations and image or video processing for painterly rendering effects.

Physically based simulation of painting [7], [8], [9] proposes different physical tool models. Brushes, even bristles, substrate, media and their interaction are then represented for use in real-time simulation applications, such as interactive painting systems. In the DAB system [10], brush head is modeled as a subdivision surface mesh wrapped around a spring-mass particle system skeleton; and the paint model incorporates variable wetness and opacity, conservation of volume, bi-directional paint transfer algorithm. It has been extended including a viscous fluid model [9] following the Navier-Stokes equations for viscous flow. An haptic system is also proposed to manipulate the paintbrush with a better interaction. Unfortunately these researches focus only on the physical-based model and most of the original work presented in theses papers are realized by an artist.

A painterly rendering effect consists in models that process in most cases images or videos in order to produce painting effects [11], [12], [13], [14], [15], [16], [17]. Litwinowicz [11] has described a model that transforms ordinary video segments into a hand-painted look. Strokes are generated with a random perturbation. Brush strokes are then oriented and rendered. Finally a frame-to-frame process is realized to move, add or delete brush strokes using a gradient-based multi-resolution technique to ensure a temporal coherence. The images produced by this technique can be considered as hand-painted, but not as impressionist style paintings.

Image Analogies [12] describes a new framework for processing images by example with a design phase in which a filter between two images is created and an application phase in which the learned filter is applied to a new target image. By choosing different types of source image pairs, a large collection of image filters can be produced during the first phase of the framework. Unfortunately this method is time-consuming and can not be used interactively.

Painterly Rendering [18], [13] proposes a basic approach where the image is painted using brushes with different sizes. Large brush strokes are used to draw a rough sketch of the image and then small brush strokes are applied only where the differences between the image and the painting are important. Paint by Relaxation [14] extends this method including a user-defined weight image and following an energy optimization strategy. The production of impressionist images remains a problem while details can not be easily described in the user-defined weight image.

Fast Paint Texture [15] proposes to simulate the physical appearance of paint strokes under lighting. A list of brush strokes and a heightmap for each stroke produce the painting heightmap. Finally a bump-mapping is used to render the painting. Also, in that case, impressionist effects are not easily reachable.

Very recently, Zhao et al. [16], [17] have presented an interactive abstract painting system. The main contribution of this work is to decompose the image into a component tree used as an entry of a painterly rendering engine with abstract operators. They consider that semantic meanings in a painting can be obtained both by the description of the scene and the artistic style. But in this method, some problems remain in the construction of the parse tree: ambiguities are addressed by asking the user to provide information through a graphical user interface.

III. Our model

In this section, we present our framework, give each step detail and show that, for some cases such as flat regions of the input image, produced results present artifacts when using our first data extraction models. An improvement is presented in the next section.

A. Framework

We aim to perform operations on original input images (usually photographs) in order to produce impressionist renderings as output of our workflow. Here, the input photograph is considered as a unique heightmap or a combination of heightmaps. As motivated above, *fractalize* the photograph — introducing fractal variations to noise the photograph details — can be a good alternative to achieve this rendering effect. In [19], Farès Belhadj presents

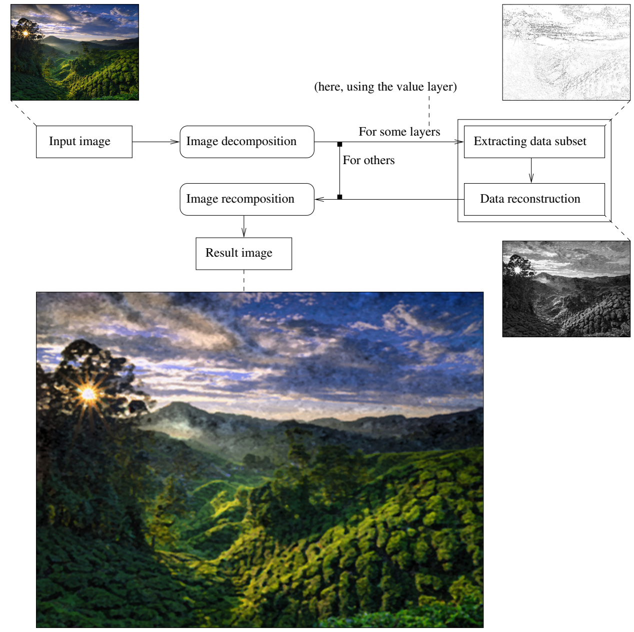

Figure 1. Our process workflow. An example color photograph is used to illustrate the result of each main step.

a constrained fractal model able to reconstruct randomly downsampled terrain heightmaps. In our work, we propose a framework where this reconstruction technique is tuned and applied to make more noisy reconstructed surfaces.

Here, in order to increase the fractal dimension of the reconstructed surface, the Hurst's exponent $\mathcal{H}$ used in the top bottom process of the MCMD algorithm [19] is set to smaller values. Usually, a better *impressionist filling* effect is obtained with an $\mathcal{H}$ parameter set to values that are less than 0.5. In return for these better *fractalization* results, *impulse noise* artifacts appear and become prevalent with the increasing of the fractal dimension. To counterbalance those high frequency variation artifacts, we apply the Tukey [20] median filter at the end of the reconstruction process and thus suppress the impulse noise effect. Finally, according to the visual results obtained with this workflow, we empirically found out that $\mathcal{H} = 0.2$ is a good approximation for the Hurst's exponent. We use this value for all results shown in this paper.

Figure 1 shows the process workflow; we use an example photograph to follow obtained results at each main step of the workflow. First, the image given as an entry of the framework (here a photograph taken from SITIS'2010 home page) is decomposed[1] into component layers according to one selected color model: RGB (Red, Green, Blue), HSV (Hue, Saturation, Value), HLS (Hue, Lightness, Saturation), etc. Some of these layers are then user-selected to go through the reconstruction process, the others are kept unchanged

[1] As there is no need to do decomposition, the grayscale images go straight to the next stage of the process.

(for the example photograph the HSV color model is used and only the Value layer is affected by the reconstruction process). Before reconstruction, layer data are resampled to higher resolution interval and a small subset of initial data is selected (methods used for characteristics extraction are discussed in the next subsection) as surface constraints for the reconstruction method. Then, the data reconstruction is done and, finally, the modified layers are resampled to the initial interval (*i.e.* where data is integer values in $[0, 255]$) and the image is recomposed using all the layers.

B. Extracting the initial data

We give to the user the ability to keep a given proportion p of the heightmap initial data. Here, a weight map can help us to select these data. Hence, initial data are sorted in descending order according to their weight and selected to fulfill the fixed p proportion. Thus, in a first approximation, we propose two distinct ways to weight initial data:

- the first weight model is based on a contour detection method that processes the photograph layers as terrain surfaces and weights, peaks and ridges positively, and holes and valleys negatively (usually we use the absolute value of the computation to weight a position). We use smooth vertex normals $\overrightarrow{N}_{x,z}$ computed using 8-connexity; then for each layer (*i.e.* heightmap) the (x, z) position is weighted using this computation :

$$w_{x,z} \leftarrow \sum_{i=1}^{8} \left(\overrightarrow{N}_{x_i,z_i} + \left(\overrightarrow{V}_{x_i,z_i} - \overrightarrow{V}_{x,z}\right)\right) \cdot \overrightarrow{N}_{x,z} \quad (1)$$

  where i denotes the i^{th} 8-connexity neighbor and $\overrightarrow{V}$ is the vertex spatial coordinates. As pretreatment, Gaussian blur can be applied to improve the quality of contours;
- the second method weights randomly all data using a uniform random number generator.

Images (b), (c), (d) and (e) of Figure 2 show first results obtained using a contour and a random data selection methods: (a) is the original color photograph, (b) is obtained by extracting contour weights from the value layer[2] (*i.e.* in the HSV color system) of (a) and keeping 10 percent of the best weighted data, (c) is the result of the value layer *fractalization* and then image recomposition (*i.e.* colorization), (e) is equivalent to (c) except for the used initial data weighting method: here, on image (d) uniform random weighting is applied.

Note that the result in (c) strengthens the contours and produces a brushstroke effect especially in regions where they are numerous. But, as we can see on the children's skin, for regions where contours are not present, the method produces a too noisy rendering. On the other hand, the result on (e) is more homogeneous but appears less expressive and seems to lack of relief.

[2]In the weight map image, white indicates low and black high weights.

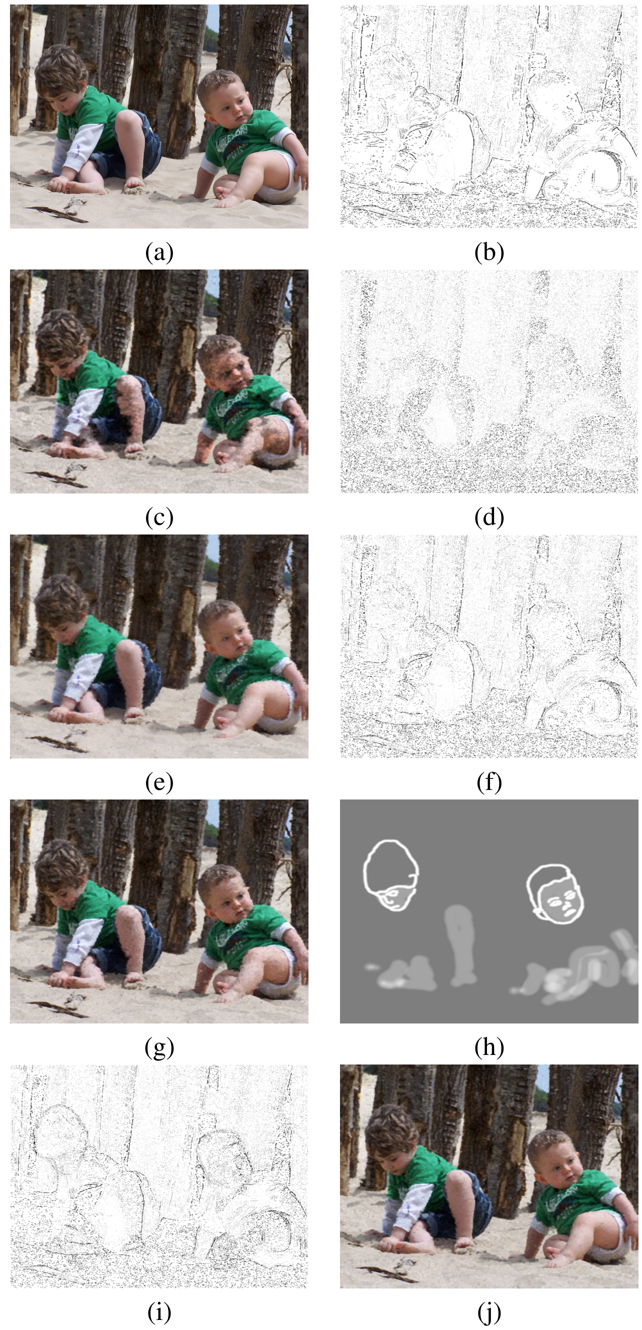

Figure 2. Data extraction and the corresponding impressionist results.

IV. Better data selection

We need to enhance the model results and produce renderings where, at the same time, contours are highlighted and flat regions or photograph details are preserved (*i.e. impressionist constraints*). Thus, we propose better models for selecting initial data.

A. Mix weightings

We propose to mix results of both selection methods presented in section III-B. The idea is to increase the probability of randomly selecting the positions located in regions where contours are not present. Thus, we start by computing weightmap for contours (ie. equation (1)), after (ie. equation (2)) we normalize theses weights[3] and finally, we add random weightings as follow:

$$w_{x,z} \leftarrow w_{x,z} + \frac{f}{1 + w_{x,z}} \times rand() \tag{2}$$

where f is a constant factor used to weight random values and $rand()$ is the uniform random number generator in the $[0, 1]$ interval. f is empirically chosen and $f = 0.15$ is used for this paper examples. Remark that the potential amount of increasing for w is bigger when w is close to 0 (*i.e.* contours are not present).

Note the results obtained for images (f) and (g) in Figure 2: image (f), as expected, presents weights where contours are mixed with random selected data. The result of reconstruction in (g) seems to converge towards what we wanted to get: enhance contours and preserve regions where they are not present.

B. User weightings

As we can see on image (g) of Figure 2, some contours of children's faces are not well preserved, and more generally, we can imagine that the user wants to preserve even more some parts of the photograph. Here, we introduce the use of a user weightmap that will strengthen the output of the previous weight computing (see equation (2)). Thus we obtain:

$$w_{x,z} \leftarrow w_{x,z} \times \left(1 + \frac{uw_{x,z}}{max_{uw}}\right) \tag{3}$$

where $uw_{x,z}$ are the weight defined by the user at the (x, z) position and max_{uw} is the greatest value in the user weightmap. Note that the user weights are not resampled in the $[0, 1]$ interval but only normalized.

Using the weightmap given on image (h) of Figure 2, we obtain, on image (i), even more initial data on the children's faces and skins. After reconstruction, we finally obtain, on image (j), a refinement of the previous results (*i.e.* image (g)) where all user-defined details are preserved.

V. Results

We experiment various combinations on several photographs and render hundreds of images. Results for some of these combinations depend on the style of processed photographs. Usually, using an HSV or an HLS decomposition, working (extracting / reconstructing) on the Value (or the Lightness) layer and then colorizing (*i.e.* recomposing) the image produces consistent results. Note that, as for results

[3]In order to take into account both ridges and valleys, we usually compute weight absolute values before normalizing.

Figure 3. Impressionist renderings (on the right) on Monet's Giverny garden photographs.

obtained in Figure 3, images presenting lot of variations produce better impressionist effects even using only the contour data extraction. On the other hand, flat regions, as such clear skies or uniform backgrounds, may produce noise clouds and need to mix weightings.

We present, in Figure 4 (a), (b), (d) and (e), various results obtained using well known photographs previously [18] used to produce impressionist effects. (d) is obtained by modifying the Value layer of the original photographs (a), face and skin details are preserved by mixing contours and random weightings. In (e) we produce an interesting expressionist effect, the noise cloud colors are well-balanced with the chameleon ones. This image is generated by applying fractal reconstruction on all HSV layers of (b). Due to the use of only contour weights, image background is strongly fractalized.

For images (c) and (f) of Figure 4, we illustrate a different result that can be easily obtained using some additional operations on the image. We generate a new surface using contours and random weightings on the Value layer of (c); then we modify the Hue layer in order to create a new atmosphere [21] by mixing the stretched-Hue layer (weighted to 0.3) with a *Sepia* hue (weighted to 0.7); finally we introduce the new image contours by multiplying the Value layer by the inverse of the contour weightings and obtain (f).

VI. Conclusion

We have presented a novel model for impressionist style painting. By keeping some of the photograph characteristics, and using them as constraints to create new images, we have shown that our surface reconstruction model is capable of producing impressionist painting effects on many photographs. Our image processing model is very simple to use, any user can intuitively produce impressionist looking renderings and do not need to manipulate any complex parameters. The model is used interactively: most example photographs used in the paper are about 400K pixels and the entire rendering process takes less than half a second per layer[4].

As future work, we aim to implement all parts of the framework as a GPU program to improve image and video treatment but also propose new renderings for 3D scenes. In that case, geometry data will help to better detect contours and flat regions.

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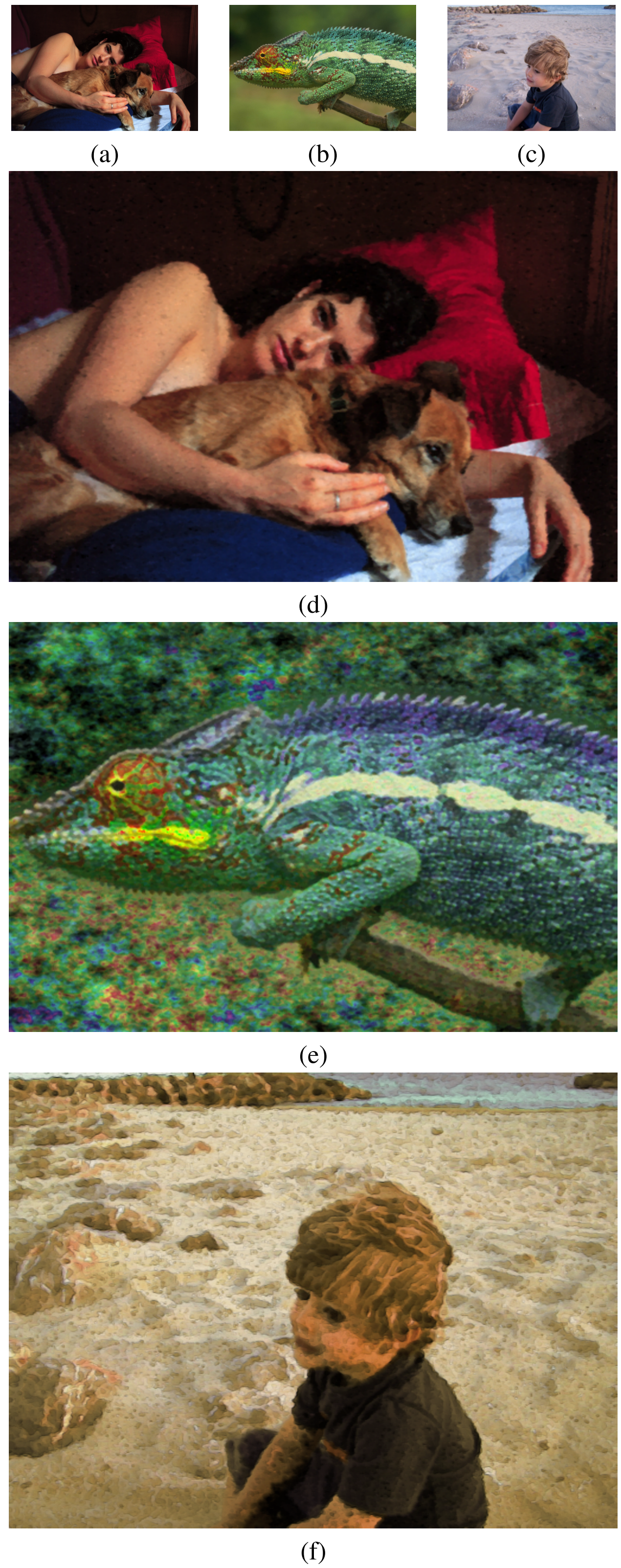

Figure 4. Impressionist style renderings of the top photographs (a) (b) and (c) (courtesy of Jon Meyer (a) and Aaron Hertzmann (b)) using our fractal-based model.