An Image Inpainting Algorithm based on K-means Algorithm

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ABSTRACT: *One of the most important fields in image processing is the image inpainting or image retouching with the aim to restore damaged images or remove a selected object from an image. Many recent works in the image inpainting focus on combining methods in order to obtain more accurate results. In this paper we proposed a new algorithm that combines K-means algorithm and the partial differential equation (PDE).*

Keywords: Inpainting, Retouching, Isophotes, Texture Synthesis, PDE, Digital Image

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1. Introduction

The main objective of image inpainting is to restore damaged images in a non-detectable way for non-familiar observer and the restoration of the missing fragments of old manuscripts allows us to safeguard the national heritage.

Other new objectives appeared such as: remove titles, or paragraphs from an image, or even in special effects: add or remove objects from the original image.

In [13] we have proposed deferent phases of our algorithm, but in this paper we discuss the necessity of the first step in our proposition with implementation détails.

This paper is organized as follows: In the next section we introduce different techniques proposed in the literature for the reconstruction of damaged pictures. Later in section three we present our contribution. In section four we present the application and in the last section we conclude this work.

2. Related Works

Recently many works introduced the digital image inpainting algorithms. Firstly, Bertalmio et al [1] proposed a new digital algorithm based on filling the corrupted area by propagating information from outside along isophotes (lines of equal gray value) direction. The user provides a mask border the inpainting area and the isophotes directions are calculated by the discretized gradient vector that gives the direction of largest spatial changes, and the information to be propagated along the isophotes direction is obtained by a smooth way of the line arriving at the gap boundary. To calculate this they used a simple discrete implementation of the Laplacian. The algorithm runs alternatively with the same steps of anisotropic diffusion [11] in order to preserve boundaries in the reconstruction. "*Figure* 1".

Oliveira et al [2] proposed a simple and faster image inpainting algorithm that uses Gauss convolution kernel.

Uhlir et al [3] used Radial Basis Functions (RBF) for the reconstruction of damaged images and to eliminate noise from corrupted images.

Chan et al [4] proposed the Total Variational (TV) inpainting model uses an Euler-Lagrange equation and inside the inpainting domain the model simply employs anisotropic diffusion based on the contrast of the isophotes.

These types of algorithms, used for inpainting small gaps, other recent works can fill large gaps based on the technique "*Texture syntheses*"

Criminisi et al [5] proposed an exemplar based on inpainting method, which fills in the target region with patches from the source region possessing similar texture. The candidate patches are selected from the whole image with special priority to those along the isophotes (lines of equal gray value) so as to preserve the linear structure during the filling-in. This process is quite similar to patch matching in texture synthesis and the fill-in priority is inspired by the partial differential equation method of physical heat flow [6].

Inspired by the work of Criminisi et al, Tang et al [6] proposed a novel texture synthesis method called coherence-based local searching (CBLS) for region filling, this method minimizes the researching area of patches in the neighbor regions which can provide sufficient information to decide what to fill, instead of researching in the whole source regions.
"*Figure* 2".

Ashikhmin et al [10] proposed an algorithm for structure synthesis, his limits need a texture model to run; to use this algorithm you must prove a texture model.

Actually, recent works focus on the use of artificial intelligence in the inpainting process in order to obtain more precise retouching.

Elango et al [7] Propose a new algorithm based on a cellular neural network. A very recent work (2011) Le Meur et al [8] proposes a new algorithm based on K-nearest neighbor algorithm.

3. Our Algorithm

In our algorithm, we tried to combine the advantages of these approaches, with the use of artificial intelligence.

Firstly, we introduce different notations used throughout this algorithm.

Let:

- I, is a damaged image with resolution $M \times N$.
- Ω, the region to fill.
- IS, the segmented image.

As preprocessing on the input image, we start by converting it to an image intensity or a gray level image, for that we use the following function in MATLAB 7

$$\boxed{\mathrm{I} = \mathrm{rgb2gray}\,(I\,).}$$

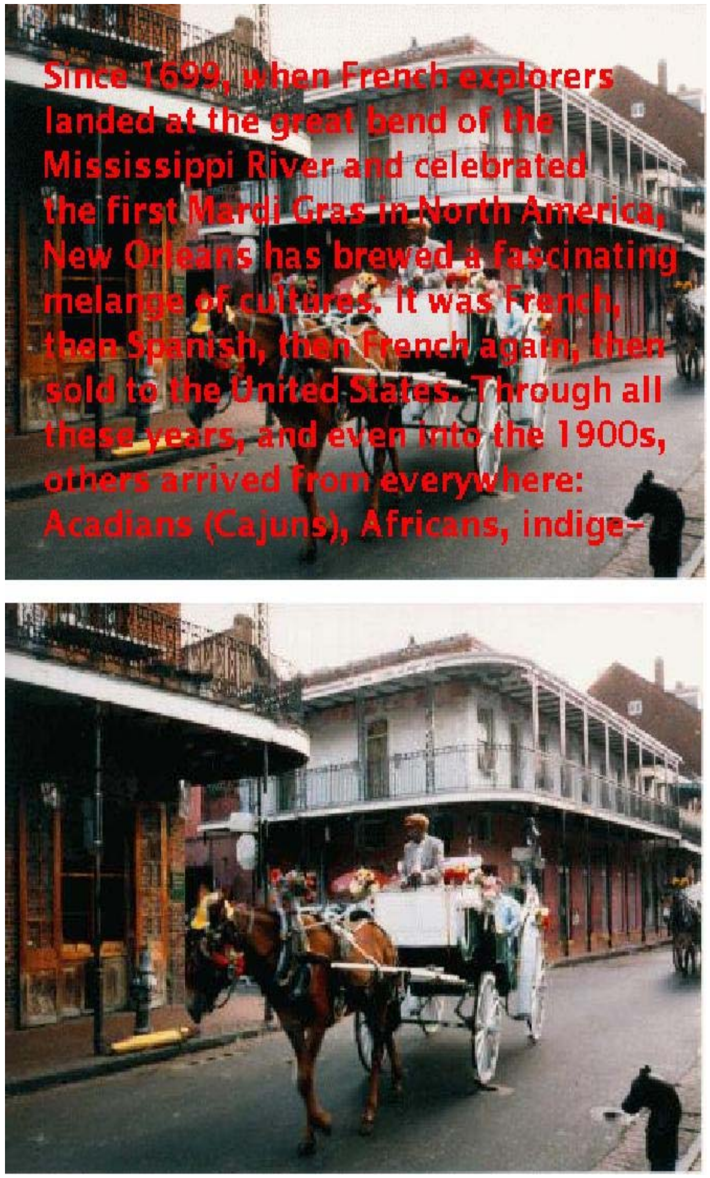


Figure1. Restoration of a color image and removal of superimposed text. [1]

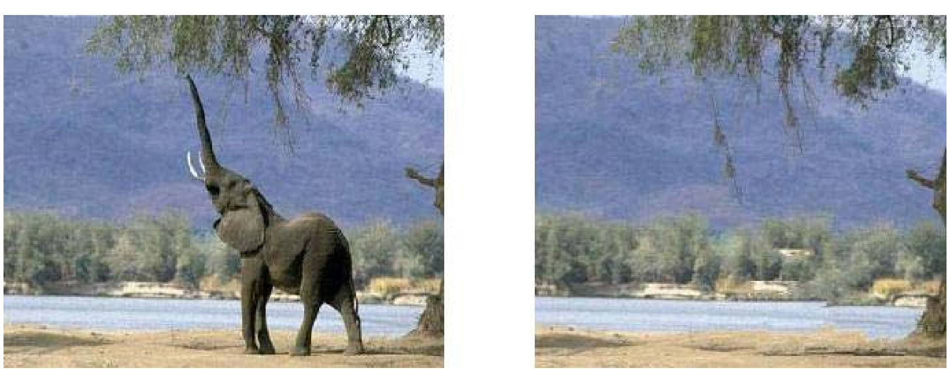


Figure 2. Removal of the elephant from the photo [6]

The algorithm has three big steps “*Figure* 3” :

The objective of the first one is to segment the original image in order to separate each texture alone.

This image will be the input of the second step which has as aim to connect every point $\boldsymbol{P_i}$ with $\boldsymbol{P_j}$ in boundary of the region $\boldsymbol{\Omega}$ to be inpainted.

Note that $\boldsymbol{P}$ is the point when two textures ($\boldsymbol{T_1}$ and $\boldsymbol{T_2}$) and the boundary $\boldsymbol{\partial\Omega}$ cross each other “*Figure* 4”.

The third step consists of the process of filling the area $\boldsymbol{\Omega}$ with the appropriate texture.

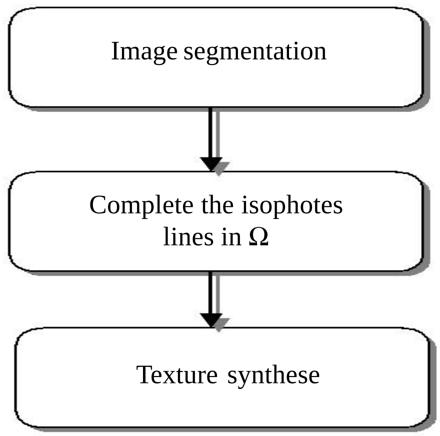


Figure 3. The 3 big steps of our algorithm

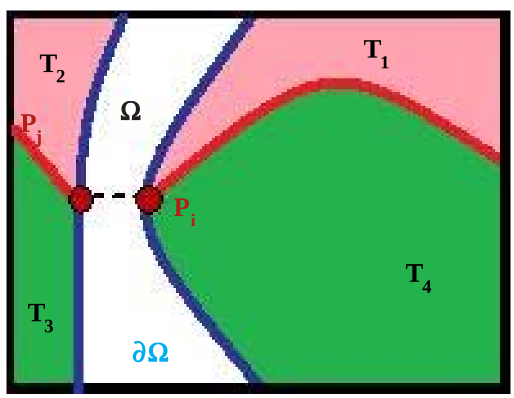


Figure 4. Description of the point P

In the next paragraph we detail each step:

3.1 The image segmention

In our proposition, to devise the original image in a group of regions, each region contains a different structure we have used the artificial intelligence K-means algorithm.

K-means is a classic tool of classification that divides a data (in our case an image) into a set of homogeneous classes, especially in terms of light intensity.

We have developed k-means algorithm in MATLAB 7

Figure “*Figure* 5”, show there results with number of classes is 5.

This phase of segmentation is very important for the next step because it minimizes the number of area surrounding Ω.

To prove this, we apply a filter “*canny*” on the original image and the segmented image, the difference between results is very clear “*Figure* 6 ”.

“*canny*” is a filter to detect edges, we have to use the following code in MATLAB7.

```
IF = edge (I, ‘canny’, [], 1);
figure;
imshow (IF, ‘notruesize’);
```

IF, is Image filtering result of the original image.

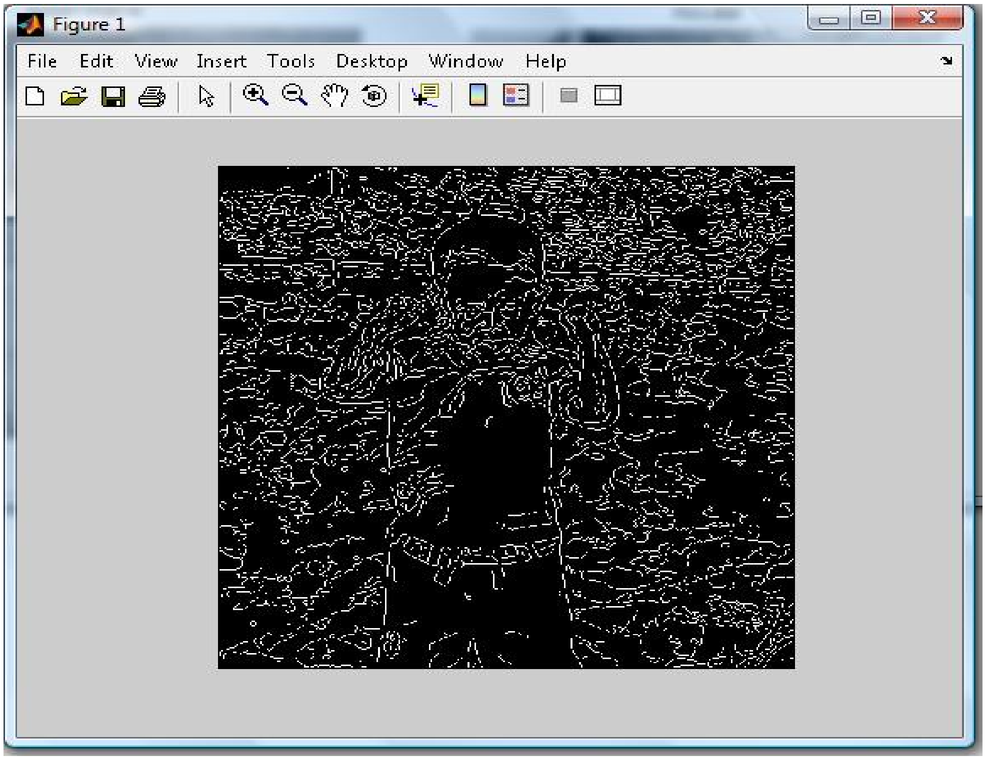
```
ISF = edge (IS, ‘canny’, [], 1);
figure;
imshow (ISF, ‘notruesize’);
```

ISF, is Image filtering result of the segmented image.

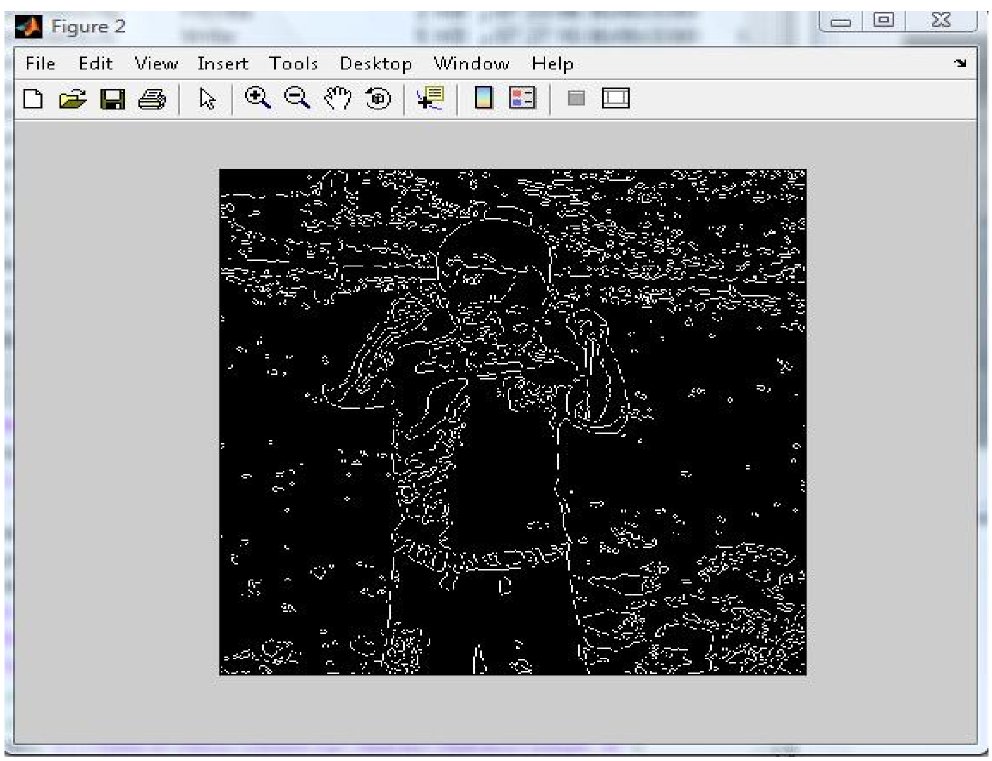
(*a*)

(*b*)

Figure 5. (a) “*ABDALLA H MECIF* ” original image.(b) “*ABDALLA H MECIF* ” Image segmented by kmeans algorithm



(*a*)



(*b*)

Figure 6. (a) "*canny* " filter on the original image, (b) "*canny* " filter on the segmented image

3.2 Complet the isophotes lines

Firstly, isophotes represents the curves of constant image intensity

- Isophote curves are tangent with the rotate of the gradient 90 degrees.
- Isophote direction = normal to the gradient
- The gradient $\nabla I = \begin{pmatrix} Ix \\ Iy \end{pmatrix}$ represents a maximum change in intensity.
- Isophots represents the minimum variation of the image intensity. "*Figure* 7".

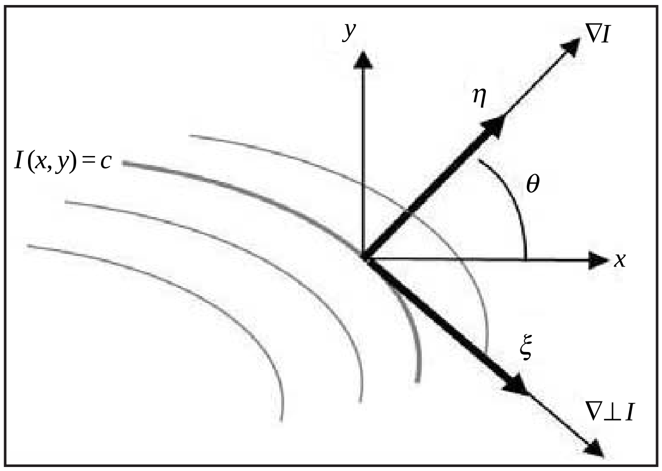


Figure 7. I $(x, y) = c$ the isophote, ∇I the gradient, and tangent [13]

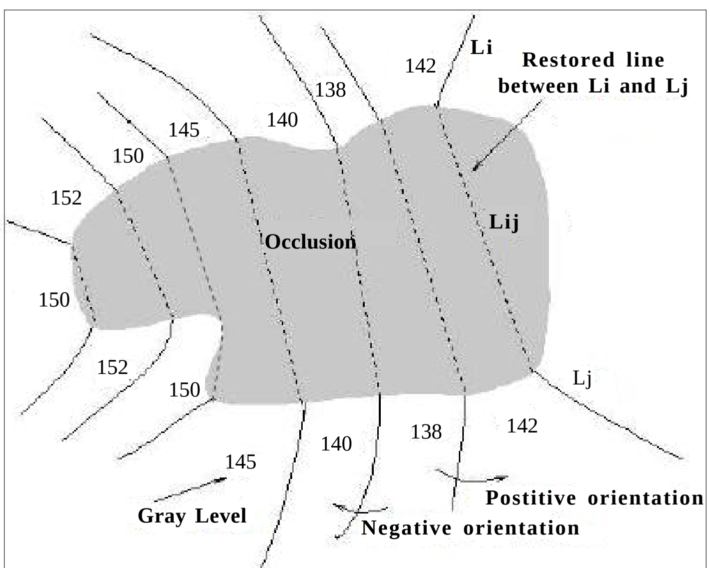


Figure 8. An occlusion and possible connection of level lines tow by tow [9] images taken from their paper

We use in this step the works of Masnou and Morel in [9] that generalizes the principle of extrapolates broken edges using elastica-type curves to the isophotes of a gray-valued image.

The principle consists of: let $L1$and $L2$ two lines arising at the boundary of the inpainting area. $L1$and $L2$ can be connected only if they have the same level and the same orientation. Since level lines can never cross, a global disocclusion will be valid if and only if this condition is satisfied see "*Figure* 8" [9].

3.3 Texture synthesis

In this step, we fill in the region **Ω** by textures that are surrounding the boundary **∂Ω** as follows:

Firstly, the region **Ω** to be inpainting is divided into $\boldsymbol{\Omega_i}$ in the same number of texture that border it (result of the second step of our algorithm).

Secondly, for each $\boldsymbol{\Omega_i}$:

If the texture T_1 that border $\boldsymbol{\Omega_i}$ in right is the same texture T_2 in his left then fill the gap $\boldsymbol{\Omega_i}$ with one of them " *Figure* 9".

Else devise the region $\boldsymbol{\Omega_i}$ in two parts in the middle then fill in its right and left side with texture that border it from the same side "*Figure* 10".

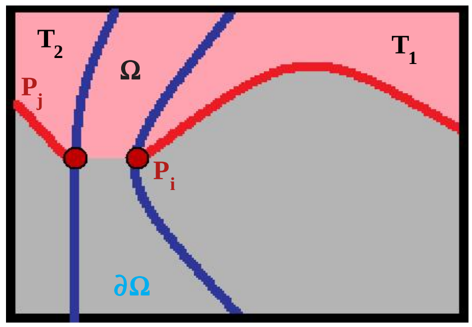


Figure 9. $T_1 = T_2$

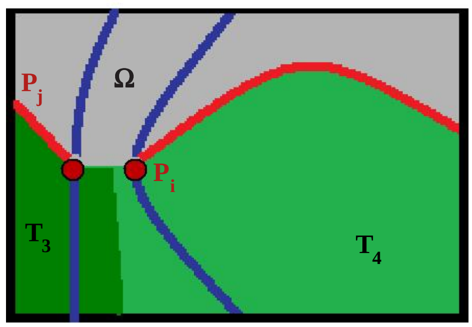


Figure 10. $T_3 \neq T_4$

4. Conclusion

In this paper, we have presented the advantages of using K-means classifier in our algorithm to determinate area around the gap to be filled. The main goal is to minimize the number of texture in order to take a definitive choice.

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