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Search Space Reduction in Exemplar Based Image Inpainting

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Abstract::- This paper aims at developing accelerated exemplary inpaint method. The feature set is considered to be the pixels along with their 8-neighbors. A Multi Phase Search Space Reduction framework namely Systematic Reduction of Information System (SRIS) is employed. SRIS, basically is a roughest based approach which imputes the missing values in an adaptive manner. In this approach the order of inpainting pixels is determined by a simple but effective priority term. The best exemplar is determined based on a similarity metric which is derived by element wise difference of informative pixels of inpaint window and the corresponding pixels of the source region window.

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I. Introduction:

Image enhancement is one of the demanding areas of image processing. A typical kind of image enhancement is known as inapint. When a mage has certain gaps either inherent or induced by the application where in an obstruction is aimed to be removed. This inpainting problem attracted several researchers for the last one decade.

The very first step in inpaint algorithm is to manually isolate the region to be inpainted. Then in order to reconstruct the image the algorithm propagates the constrained information, structural as well as textural available in the vicinity of the inpaint region along the level lines. Based on this aspect inpainting algorithms are broadly classified into three categories. The first category algorithms [1 2 3 4] aim at preserving the structural features like edges and contours of the image. These methods make use of PDE and TV models. But these methods work well for smaller and linear structures. One of the main issues with such techniques is that it is restricted to using the information in the vicinity of target region. Therefore, in many situations where the local information does not characterize the missing information, the resulting reconstructed information in the missing region will not be visually consistent with the rest of the image. In addition to these issues PDE based methods tend to blur the inpainting domain due to their inherent characteristic. Along sides, a general framework for combining of variational methods and wavelet analysis is developed by Julia A. Dobrosotskaya[10] . This frame work utilizes wavelets to store sharp features in the image. Then variational formulation helps to evolve the image while using the stored features.

The second class of algorithms [5 6] aim at texture interpolation. These algorithms regenerate the textures by utilizing the samples from the source region.

The last class of methods consists of the *exemplar-based* techniques[7 8], which are considered to be most successful techniques up to now. These methods try to fill the unknown region simply by copying content from the known and identified part of the image. These methods are mainly used for the purpose of texture synthesis. Jia *et al.* [11] have presented a technique for filling image regions based on a texture-segmentation step and a tensor-voting algorithm for the smooth linking of structures across holes. Their approach has a clear advantage in that it is designed to connect curved structures by the explicit generation of subjective contours, over which textural structures are propagated. On the other hand, their algorithm suffers from expensive segmentation step, and requires a hard decision about what constitutes a boundary between two textures. Recent exemplar-based methods, that are our techniques of interest also place emphasis on the order by which the image inpainting proceeds, using a priority term for this purpose [9]. However, this method is computationally hungry because of huge search for best match, for a given element of target region of the image. This expensive method can be made computationally effective by reducing the search space and appropriate distance of similarity for the best match. This paper aims at reduction of search space by, a greedy strategy adaptive similarity metric within source region objects.

II. Methodology:

The main contribution of this paper is, a novel approach, to develop a enhanced frame work for reducing the time complexity of priority based exemplar method while preserving the structures and generating the textures. We start our frame work by coming out with a tabular form representation of image, which is going to serve as Information System. For this, three types of records are generated from the given image, the first category (CI) being the 8-naighbor for which Centre pixel value is not defined. The second category of records (CB) is records with 8-naighbors along with Centre pixel for which value is known but few neighborhood values are undefined. In these two records the missing attribute value is set to be a large value like 1000. And the third category of records (CS) is the set of all 8–neighbors along with the centre pixel for which all the pixels values are defined. Here onwards we use words record and touple interchangeably. In the context of inpaint problem third category pixels are treated as source

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pixels. The other two categories are considered to be inpaint pixels. In this problem, second category pixels are treated as boundary pixels. We can put the above set of records represented into a table that stands for Information System in the given image. Thus we have an incomplete Information System. By considering the third category pixels (CS), we attempt to fill the missing pixels values. This we call as Systematic Reduction of Information System SRIS. We build the Knowledge using this SRIS. We, also extract rules forcing the central pixel attribute as conditional attribute. These rules are used for the purpose of estimating missing values that do stand for unknown pixels of the image. This process is applied in iterative fashion and there by eventually we end up with no touple with missing values. The corresponding image will be referred as inpainted image.

The steps involved in this frame-work are

1. Reduction of Search space size by histogram.
2. Determine the order of infilling by working on touples from CB with least number of unknown values and sharp changes among the known pixel values.
3. Localizing best exemplar discovery by applying adaptive thresholding rule.
4. Estimating the missing values using element-wise difference of pixel values.
5. Repeat from 2-4 until there are no records left in CI.

Now we elaborate these steps. To start with, we have at hand is the Information system in which CS records are divided into 30 bins based on the centre pixel value and histogram is generated against these bins. Important point is, here onwards the centre pixel plays an important role in decision making. It is very easy to perceive that step 1 stands for the first step in multi stage reduction of search space. Now, a record from CB is selected with least number of unknown pixel values and sharp change in the known pixel values. Let us denote this record with CB_T. This forms step 2 in our frame work. Supposing that the centre pixel of this record happened to fall in bin B_d which has a frequency f_d, then we proceed to further localizing the exemplary search, with in B_d, by defining a qualitative metric namely degree of freedom. This degree is determined by bin frequencies. Let the B_{min} be the bin with minimum frequency f_{min} . Now we define the degree as

$$\text{degree} = \text{ceil}\left(\left(f_{min} \;/\; f_d \right) * 5 \right) \text{ i.e. degree} \in \{1,2,3,4,5\}$$

The utility of degree is to choose touples from B_d that are with in the degree of freedom with reference to centre pixel value. Let us denote such a set of touples with CS_T. This degree indicates adaptive threshold. This accomplishes the step 3 in our frame work. In the last step of our algorithm, we compute the element wise difference between informative pixel values of CB_T and the corresponding pixels of every touple of CS_T. Then, the touple with least number of deviations within the specified degree is considered to be the best exemplar record. This measure gives good results relative to pure and widely used, Criminsi's L_2 norm [9] based distance measure. We repeat the steps 2 to 4 so long as there are records in CI. This concludes the algorithm.

In the next section we present the results of our method.

III. Results:

In the following section we present the results of our frame work.

In our experiments we have taken text removal application to demonstrate the results.

Figure 1 original Image 1

Figure 2 Mask

Figure 3 Inpaint Image 1

Conclusion: In this paper the best exemplar based inpainting method is improved by introducing granular approach to remove the search space and to locate the best exemplar. The results confirmed that the histogram approach is capable of solve large scale text removal problems.

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