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INPAINTING FOR LAZY RANDOM WALKS SEGMENTED IMAGE

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Abstract: **Inpainting is art of reconstructing the missing portions of images in order to make it more legible and to restore its unity .The aim is to create a software that can remove selected portions from the image and fill the hole left behind in a visually plausible way using the background information. When we take a snapshot, there may be some unwanted object that comes in between. There is a need of software that can efficiently remove the marked object from the image. Inpainting is done on a Lazy Random Walk Segmented Image. The proposed method computes the priority of the target patches using robust priority function and finds the best matching source patch. Also the objective for image inpainting is not to recover the original image, but to create some image that has a close resemblance with the original image.**

Keywords: **Inpainting, software, snapshot, object, method, original image.**

I. INTRODUCTION

Image reconstruction is a robust means by which the underlying images hidden in blurry and noisy data can be revealed. The main challenge is sensitivity to measurement noise in the input data, which can be magnified strongly, resulting in large artifacts in the reconstructed image. The cure is to restrict the permitted images.Different methods are available for image reconstruction.

Inpainting, the technique of modifying an image in an undetectable form. Also inpainting or retouching, this activity consists of filling in the missing areas or modifying the damaged ones in a non-detectable way by an observer not familiar with the original images. The algorithm effectively hallucinates new colour values for the target region in a way that looks “reasonable” to the human eye.

Our LRW algorithm with self-loops effectively solves the segmentation problem in weak boundary and complex texture regions. On the otherhand, the LRW based superpixel algorithm may suffer from the sensitiveness of the initial seed positions. In order to overcome these limitations and improve the performance, we further develop a new superpixel optimization approach by introducing an energy optimization framework. Our superpixel optimization strategy is essentially a compactness constraint, which ensures the resulting superpixels to distribute uniformly with the homogeneous size by relocation and splitting mechanism. Our energy function is composed of two items, the first data item adaptively optimizes the positions of seed points to make the superpixel boundaries adhere to the object boundaries well, and the second smooth item adaptively divides the large superpixels into small ones to make the superpixels more homogeneous.

However, each superpixel method has its own advantage and drawback that may be better suited for a particular application. It is still challenging to develop a high quality superpixel algorithm, which avoids the under-segmentation and locally groups the pixels respecting the intensity boundaries. we develop a new image superpixel segmentation method by the lazy random walk and energy optimization algorithm to achieve better performance than the previous approaches.

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II. LAZY RANDOM WALK ALGORITHM

Superpixels are commonly defined as contracting and grouping uniform pixels in the image, which have been widely used in many computer vision applications such as image segmentation and object recognition. The superpixel segmentation can be considered as a pixel labeling problem where each superpixel is assigned to a unique label. Our approach begins with placing the initialized seeds of the assigned superpixels. Then, we use the LRW algorithm to obtain the initial superpixels and their boundaries. Our superpixel approach consists of two main steps. The first step is to obtain the superpixels using the LRW algorithm with initial seed points. In order to improve the superpixel performance, we optimize the initial superpixels by the new energy function in the second step. Our energy includes two items: the data item makes the superpixels more homogenous with regular size by relocating the seed positions, and the smooth item makes the superpixels more adhering to the texture edges by dividing the large irregular superpixels into small regular ones.

LRW Based Superpixel Initialization:

Our method begins by placing the initial superpixel seeds on the input image where we follow the similar seed initialization strategy.

Input: Input image $I(x_i)$ and an integer of initial seeds K
step 1. Define an adjacency matrix $\mathcal{W} = [w_{ij}]_{M\times N}$
step 2. Construct the matrix $S = \mathcal{D}^{-1/2}\mathcal{W}\mathcal{D}^{-1/2}$
step 3. Compute $f_{l_k} = (I - \alpha S)^{-1} y_{l_k}$
step 4. Compute $R(x_i) = \underset{l_k}{argmax}\, \mathcal{CT}(c_{l_k}, x_i)$ to obtain the labels by assigning label $R(x_i)$ to each pixel x_i.
step 5. Obtain superpixels by $S_{l_k} = \{x_i | R(x_i) = l_k\}$ where $\{i = 1, \cdots, N\}$ and $\{k = 1, \cdots, K\}$
Output: the initial superpixel results S_{l_k}.

Superpixel Optimization:

By considering the compactness constraints, we further improve the performance of superpixels with the following energy optimization function:

$$E = \sum_l (Area(S_l) - Area(\bar{S}))^2 + \sum_l \widetilde{W}_x \mathcal{CT}(c_l^n, x)^2$$

Input: Initial superpixels S_l and an integer N_{sp}
step 1. Apply Equation (12) to obtain the new c_l^n
step 2. Apply Equation (17) to get the new $c_{l_{new},1}$ and $c_{l_{new},2}$
step 3. Refine S_l by Equation (9) with c_l^n, $c_{l_{new},1}$ and $c_{l_{new},2}$
step 4. Run steps 1 to 3 iteratively until convergence
Output: the final optimized superpixel results

Since the LRW method considers the global relationship well between all the seeds and each pixel, it can solve the weak boundary and complex texture problems very well and obtain the super pixels with good performance. The super pixel results by our LRW algorithm are better than the results by the original RW algorithm. Furthermore, our super pixel optimization algorithm plays an important role to relocate the seed positions and create the new seeds after splitting process, which further makes the regularity and boundary adherence of final super pixels by our LRW algorithm.

III. CONCLUSION

Large areas with lots of information lost are harder to reconstruct, because information in other parts of the image is not enough to get an impression of what is missing. therefore the objective for image inpainting is not to recover the original image, but to create some image that has a close resemblance with the original image. Here the segmentation results

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provides local texture similarity and dominant structure region and then we adaptively choose weighting parameter values of the robust priority function for each segment. With these information of a segmented image, it determines the suitable patch size and selects candidate source regions for reducing unnatural artifact.. With this approach we can reduce the number of iterations and error propagation caused by incorrect matching of source patch.

We can revert deterioration using inpainting .Using inpainting, we can remove unwanted objects, text, etc. from the image. If extended to video inpainting, it would be able to provide a great tool to create special effects etc.

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