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An Isotropic Approach for Image Patching

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ABSTRACT: The ability to compare image regions (patches) has been the basis of many approaches to core computer vision problems, including object, texture and scene categorization. Developing representations for image patches has also been in the focus of much work. However, the question of appropriate similarity measure between patches has largely remained unattended. This work introduces the image patching, where an image is broken into non-overlapping patches, and modifications or constraints are applied in the patch domain. A modified image is then reconstructed from the patches, subject to those constraints. When no constraints are given, the reconstruction problem reduces to solving a jigsaw puzzle. Constraints that may specify include the spatial locations of patches, the size of the output image, or the pool of patches from which an image is reconstructed. The resulting image reconstructions show the original image, modified to respect the user's changes. Here we apply the patch transform to various image editing tasks and show that the algorithm performs well on real world images.

Index terms: Patching, Denoising, spatial location, illumination, Bregman.

I. INTRODUCTION

A user may want to make various changes to an image, such as repositioning objects, or adding or removing textures. These image changes can be difficult to make using existing editing tools. Consider repositioning an object. It first must be selected, moved to the new location, blended into its surroundings, then the hole left where the object was must be filled-in through texture synthesis or image in painting. Even after these steps, the image may not look right: the pixels over which the object is moved are lost, and the repositioned object may not fit well in its new surroundings. In addition, filled-in textures may change the balance of textures from that of the original image. It would be more convenient to specify only the desired changes, and let the image automatically adjust itself accordingly. The usual practice is to find the best patch locally and then to copy it to the hole region. However, since the best patch is fixed in size, it is hard to adapt these methods efficiently either to various patterns or to content synthesis for image completion. Meanwhile, the image structures can provide additional prior information for the image completion problem. Some existing methods may cause discontinuities in the salient structures. Thus, an automatic image completion should estimate and propagate the salient structures to guide the essential process of texture synthesis [2]. The detection of image edges has been one of the most explored domains in computer vision. While most of the effort has been aimed at the detection of intensity edges, the study of color edges and the study of texture edges are also well developed fields. The patch transform is well suited for controlling the amount of textures, or the patch statistics, in an image. One method of manipulating the patch statistics is by explicitly controlling how many patches of a certain class appears in the image.

If patches are too small, the patch assignment algorithm breaks down due to exponential growth in the state dimensionality. A simple extension to address this issue is to represent the image with overlapping patches, and generate the output image by 'quilting' these patches .Could define the compatibility using the seam energy. Since seams can take arbitrary shapes, less artifact is expected. Another limitation of this work is the large amount computation. To enable an interactive image editing using the patch transform, both the number of iterations and the amount of computation per iteration should be reduced.

II. EARLIER WORK

Liu *et.al.* (2016) [1] have used hybrid regularizes-based adaptive anisotropic diffusion method for image denoising. They used the method to eliminate the stair casing effect for total variation filter and synchronously avoid the edges blurring for fourth order PDE filter. They use non–linear method which have a good balance between noise removal and edge preserving. They proposed an adaptive diffusion model for image denoising which is composed of a hybrid regularization.

Experiment show that proposed model can preserve important structure such as edge and corner.

Taeg Sang Cho *et al* (2011) have used the image patching to demonstrate that the patch transform can be used in several image editing operations. The patch transform provides an alternative to an extensive user intervention to generate natural looking edited images. It has to specify two inputs to reconstruct an image: the bounding box that contains the object of interest, and the desired location of the patches in the bounding box. the algorithm is robust to changes in the size of the bounding box. That found it the best to fix as small a region as possible if the user wants to fully explore space of natural looking images. However, if the user wants to generate a natural-looking images. However if the user wants small iterations he has to take a larger region in the image.

Jose M. Celaya-Padilla *et. al.* (2012) have demonstrated the texturing patching process includes a variety of issues such as access, sampling, and filtering, texture patching is the process to translate one texture to an image, this is commonly used to extract objects from an scene, and fill full the empty area with some texture that blend with the rest of the image, this can be found widely on animated movies, videogames and digital content. The mapped image, usually rectangular, is called a texture map or texture, and is used to generate a new texture, of N by M size, which fill full the image [3].

David Harbater (1999) has evaluated method the rigid approach to patching is often regarded as more intuitive than the formal approach, its foundations are less well-established. But constructions involving the formal approach have tended to be technically more cumbersome. The purpose of the current paper is to build on previous formal patching results to create a framework in which such constructions are facilitated. In the process we prove a result asserting that singular curves over a field that can be thickened to curves with prescribed behavior in a formal neighborhood of the singular locus, and similarly for covers of curves. Afterward, we obtain applications to fundamental groups of curves over large fields [4].

Idan Ram (2013) proposed work took a different approach, and proposed a denoising scheme which consists of reordering the noisy image pixels to what should be a 1D regular signal, and applying it linear smoothing filters. Then applied several permutations to the image, each was obtained by calculating distances between the noisy image patches, and ordering them such that they were chained in the shortest possible path, essentially solving the traveling salesman problem. They note that similar permutations were employed in Generalized Tree-Based Wavelet Transform and Redundant Wavelets on Graphs and High Dimensional Data Clouds to construct image-adaptive wavelet transforms, which were used for image denoising [5].

We wish to modify the NL-means algorithm [2] so it will make use of these signals. The NL-means algorithm estimates each pixel $\hat{y}[n]$as a weighted average of pixels in Z, which reside in a square neighborhood S_n^{NL} surrounding z[n].

The weights are determined by the distances between the patch surrounding the estimated pixel

and the patches surrounding the pixels in

$$\hat{y}[n] = \frac{1}{D_n} \sum_{m \in S_n^{NL}} z[m] w_{n,m}$$

where the weights D_n and $w_{n,m}$ satisfy

Henry Adams *et.al* (2009) have shown that their analysis by constructing data sets of high contrast patches, where high contrast is dened by threshholding a natural measure of contrast [6]. They found that high contrast 3×3 range patches are densely clustered around the binary patches. A pixel in a binary range patch is one of two values: foreground or background. For optical patches, Lee *et al* and a strikingly different distribution: the majority of the high contrast patches lie near a 2-dimensional annulus. Each patch on this manifold is a linear step edge, a few of which are Step-edge annulus and Primary circle. The annulus is parameterized by the angle of the edge and by the distance of the edge from the center of the patch. The range patches simply broke up into clusters without an obvious simple geometry, while the optical patches were organized in a clearly geometric way. Our hypothesis concerning this conclusion is that it is due to the clustering of the range patches around binary patches: after normalizing the contrast, essentially only two values are taken in range patches, whereas up to nine values are taken in optical patches.

Nearest patch search algorithms can be roughly classified into two categories: the exact nearest patch matching and approximate nearest patch matching. PCA Trees, K-means, are often used to achieve exact nearest patch matching. Currently, there are several methods, such as Kd-Tree [9], ANN, TSVQ and Vantage Point Trees, that can perform both exact and approximate nearest patch matching. All these methods apply hierarchical tree structure to accelerate searching.

III. PROPOSED SOLUTION

The main limitation identified is that the control over the patch location is inherently limited by the size of the patch, which can lead to visible artifacts. If patches are too small, the patch assignment algorithm breaks down due to exponential growth in the state dimensionality. A simple extension to address this issue is to represent the image with overlapping patches, and generate the output image by quilting these patches.

It could define the compatibility using the seam energy. Since seams can take arbitrary shapes, less artifact is expected. Another limitation recognized is the large amount of computation. To enable an interactive image editing using the patch transform, both the number of iterations and the amount of computation per iteration should be reduced. The overlapping patch transform framework may help in this regard as well since larger patches (i.e. less patches per image) can be used without degrading the output image quality.

Bregman's method is an iterative algorithm to solve certain convex optimization problems. The algorithm is a row-action method accessing constraint functions one by one and the method is particularly suited for large optimization problems where constraints can be efficiently enumerated. The algorithm starts with a pair of primal and dual variables. Then, for each constraint a generalized projection onto its feasible set is performed, updating both the constraint's dual variable and all primal variables for which there are non-zero coefficients in the constraint functions gradient. In case the objective is strictly convex and all constraint functions are convex, the limit of this iterative projection converges to the optimal primal dual pair. The method has links to the method of multipliers and dual ascent method and multiple generalizations exist.

The Anisotropic Diffusion algorithm came up with the best choice among the various options at each step, describing a complete image adapted denoising tool. The estimation of two gradient threshold parameters using the knee algorithm improves the adaptability of the filter, yielding stronger edges as the estimation of one parameter tends to over smooth the image. This property also introduces a sense of directionality which could lead to a comparison with a filter class that smoothes differently along distinct directions. Such anisotropic filters are usually modeled by diffusion tensors instead of scalar-valued diffusions [7-8] and are widely used in images with strong oriented structures, such as seismic or medical images.

The steps of Image patching algorithm:

Step1: Input a Noisy(Distorted, broken, damaged and missing pixel) Image and Compute σ of the most uniform block of pixels.

Step2: Given σ Construct the discrete Gaussian filter Gσ.

Step 3: Compute the Following:

1. The original image I is convolved with the kernels of the Sobel operator and N edges with the highest gradient magnitudes are chosen. In order to choose edges that belong to different edges with in the image, a minimum Euclidean distance D between any pair of edges considered is required.

Image denoising: The steps involved in image denoising is

Step 1: Blur the image with Gaussian function.

Step 2:Decomposition of image into patches to form dictionary.

Step 3:The similar patches could form clusters.

Step 4:The singular value decomposition is used to learn dictionary.

svd(A)= USV

where A= input image

U= rows entries of image patch

V= column entries of image patch

S= diagonal entries containing Eigen vectors.

Step 5: Split Bregman iteration of patches onto the image to restore the image.

Step 6: The dictionary and sparse coding coefficients updated at the end of final iteration.

Step 7: Image updated by using resulted dictionary.

Experimental PSNR and MSE Values in dB for Patch Noise 20 dB.

Table 1.

Data Set Images	Existing Method		Proposed Method	
	PSNR (db)	MSE (db)	PSNR (db)	MSE (db)
Lena	23.15	298.12	25.76	290.0
Barbara	22.79	292.06	24.60	288.08
Peppers	23.47	299.12	25.97	290.84
Mandrill	23.65	300.39	25.22	291.80

IV. CONCLUSION

The algorithm would perform well on a diverse set of images, it will break down under two circumstances If the input image lacks structure such that the compatibility matrix is severely non-diagonal, the reconstruction often assigns the same patch to multiple nodes, improves the local evidence. Another typical case arises when it's not possible to generate a plausible image with the given user constraints and patches. This work analyzes how the proposed algorithms affect the synthesized speed and quality, and considers texture to be a nature stochastic image. As compared to other methods, our proposed method gives better results.

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