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# Literature Review on Image Processing Using Smooth Ordering of its Patches

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***Abstract- In this review paper, we explore alternative approaches to non-locality, with the goals of i) developing universal approaches that can handle local and non-local constraints and ii) leveraging the qualities of both non-locality and sparsity. For the first point, we will see that embedding the patches of an image into a graph-based framework can yield a simple algorithm that can switch from local to nonlocal diffusion, which we will apply to the problem of large area image inpainting. For the second point, we will first study a fast patch pre-selection process that is able to group patches according to their visual content. This pre-selection operator will then serve as input to a social sparsity enforcing operator that will create sparse groups of jointly sparse patches, thus exploiting all the redundancies present in the data, in a simple mathematical framework. we will study the problem of reconstructing plausible patches from a few binarized measurements. We will show that this task can be achieved in the case of popular binarized image keypoints descriptors, thus demonstrating a potential privacy issue in mobile visual recognition applications, but also opening a promising way to the design and the construction of a new generation of smart cameras.***

***Keywords*-Patch Based Processing, Pixel Permutation, Denoising, Inpainting.**

## I. INTRODUCTION

Patch models create a representation of a category of input data by creating a set of patches that represent all of the constituent parts of the given category of input data. For example, a category of input data can be a particular kind of images, such as images of human faces. A significant advantage of patch models is that each constituent part of a category of data needs only one patch. Thus, because there will often be a large amount of repetition within the data in a category, a patch model can be much smaller than the data it is representing and still capture every aspect of the represented category of data. Because of the benefits provided by patch models, the use of such models is increasing in popularity. Specifically, patch models for images have recently seen increased use for various low level image processing tasks [8]. This research introduces principled, broadly applicable, and efficient patch-based models for data processing applications. These models work across many different applications, including novel ones, even without any domain knowledge because of their principled probability models that require minimal parameter tuning. While this study shows for a number of applications, the results are primarily to demonstrate the broad applicability of the models, which are able to be applied to these varied tasks by optimizing under their probability models. This research is not focused on any one particular application, but rather, the primary contribution is the models.


Fig.1. Shows the Noisy and Original Image

Recently, "epitomes" were introduced as patch-based probability models that are learned by compiling together a large number of examples of patches from input images. The image epitome model is appealing in that its principled generative model allows for various modelling and reconstruction tasks. While powerful, the model is lacking in some aspects that restrict its practical usage. This research extends the epitome model in several ways and proposes it as a novel patch model platform for analyzing visual data and performing various tasks with the data. A background on patch models and the image epitome model. Two of the key parameters of the epitome model are the epitome size and patch size, which have dramatic effects on the ability of the epitome to model the data, yet prior work has not provided any guidance in terms of selecting these parameters. These parameters are studied using natural image statistics to gain a better understanding of them. Learning and inference with epitome models are a computationally intensive procedure, so a novel, efficient algorithm is introduced that dramatically reduces the computational complexity of the patch comparisons necessary in the epitome model. The epitome model was originally presented as a model for image data. The model is extended to videos by using 3D patches from the video, while also presenting a novel way to model missing data. The use of the extended model is then applied to applications of video super-resolution, video interpolation, object removal, and denoising. The epitome model, like other patch models, capture local correlations between pixels in a patch. Thus, if a patch in a first image matches well with a patch in a second image, then a second patch in the first image that shares pixels with the first patch should also match well to a similarly displaced second patch in the second image. Conventional image processing applications can use these local correlations to piece or cluster together groups of patches to form textures that can then be used to process portions of an image.

## II. PRIOR PATCH-BASED METHODS

An algorithm is said to be non-local when the considered primitives are patches, and examples of patches are searched in the entire input data, without considerations of spatial relationship. The so called non-local algorithms will exploit the same ideas as examplebased methods: exploring the whole image in order to detect redundant patches (the examples) that will be processed jointly, thus preserving the textures (because of their redundancy) while ignoring the noise (that is itself too random to be captured as a redundancy).

*The intuition behind non-local denoising*

Denoising as averaging. Let us start with a simple example. Suppose that we want to estimate the value of some constant phenomenon (a pressure, a temperature..). Author have taken n independent measures $f\{x\}_{i=1}^{n}$ that are corrupted by some additive random noise. Obtain a good estimate of the underlying value. A simple answer can be found in any introductory Probability textbook: since the noise is random, the empirical mean M(x) defined by

$$M(x) = \frac{1}{n}\sum_{i=1}^{n} x_i$$

A good estimator of the true value, and the variance of the noisy measurement is reduced by a factor $\sqrt{n}$. Directly translated to images by assuming that connected pixels were likely to represent the same object, this simple method has led to local averaging schemes, that effectively remove some noise but at the cost of introducing some undesirable blur on textures and at the edges of objects. It is that this simple denoising approach is so destructive regarding the image content. It is because the images do not meet previously made fundamental assumptions: all the pixels acquired do not represent the same physical phenomenon (color, amount of light) in the observed scene. Hence, blindly averaging pixels just because they are spatially close leads to mixing unrelated colors or light intensities and eventually introduces blur.

## III. LITERATURE REVIEW

I. Ram, M. Elad and I. Cohen [1] proposed an image processing scheme based on reordering of its patches. For a given corrupted image, authors extract all patches with overlaps, refer to these as coordinates in high-dimensional space, and order them such that they are chained in the "shortest possible path," essentially solving the traveling salesman problem. The obtained ordering applied to the corrupted image implies a permutation of the image pixels to what should be a regular signal. This enables us to obtain good recovery of the clean image by applying relatively simple one-dimensional smoothing operations (such as filtering or interpolation) to the reordered set of pixels. Authors explore the use of the proposed approach to image denoising and inpainting, and show promising results in both cases.

D. Lin and J. Fisher [2] presented a new generative image model, integrating techniques arising from two different domains: manifold modeling and Markov random fields. First, authors develop a probabilistic model with a mixture of hyperplanes to approximate the manifold of orientable image patches, and demonstrate that it is more effective than the field of experts in expressing local texture patterns. Next, authors develop a construction that yields an MRF for coherent image generation, given a configuration of local patch models, and thereby establish a prior distribution over an MRF space. Taking advantage of the model structure, authors derive a variational inference algorithm, and apply it to low-level vision. In contrast to previous methods that rely on a single MRF, the method infers an approximate posterior distribution of MRFs, and recovers the underlying images by combining the predictions in a Bayesian fashion. Quantitatively demonstrate superior performance as compared to state-of-the-art methods on image denoising and inpainting.

D. Zoran and Y. Weiss [3] presented a learning good image priors are of utmost importance for the study of vision, computer vision and image processing applications. Learning priors and optimizing over whole images can lead to tremendous computational challenges. In contrast, when authors work with small image patches, it is possible to learn priors and perform patch restoration very efficiently. Authors compare the likelihood of several patch models and show that priors that give high likelihood to data perform better in patch restoration. Motivated by this result, authors propose a generic framework which allows for whole image restoration using any patch based prior for which a MAP (or approximate MAP) estimate can be calculated. Authors show how to derive an appropriate cost function, how to optimize it and how to use it to restore whole images. Finally, authors present a generic, surprisingly simple Gaussian Mixture prior, learned from a set of natural images. When used with the proposed framework, this Gaussian Mixture Model outperforms all other generic prior methods for image denoising, deblurring and inpainting.

N. Arora and P. Kalra [4] done researched on Digital in painting is the technique of filling in the missing regions of an image using information from the surrounding area in a visually indistinguishable way. In this paper, authors try to improve the Exemplar based method by manipulating the values of various parameters like patch size, shape and size of the mask. Authors present an analysis of the impact of various geometric parameters on the quality of in painted images. Image denoising refers to the removal of unwanted noise from the images. In most cases, the images which need to be in painted are noisy, which makes it necessary to eliminate noise and fill in the missing regions from neighboring pixels. Therefore, filling in of missing regions and removal of noise are the two very important topics in image processing. This paper also addresses the issue of performing both in painting and denoising simultaneously using two different approaches: pipelined approach and interleaved approach. The effectiveness of these approaches is demonstrated with a number of results on various images.

Z. J. Zhu, Z. G. Li, S. Rahardja and P. Franti [5] presented a novel method of high-quality image inpainting for recovering an original scene from degraded images using reference images of different exposures is proposed. It consists of a new inter-pixel relationship function and the respective refinement to synthesise missing pixels from existing spatially co-related pixels, and a dual patching to minimise the noise caused by dynamic range lost. Experiments on the method have been conducted and the results demonstrate the reliability of the proposed method.

X. Li and Y. Zheng [6] presented a patch-based variational Bayesian framework for video processing and demonstrate its potential in denoising, inpainting and deinterlacing. Unlike previous methods based on explicit motion estimation, authors propose to embed motion-related information into the relationship among video patches and develop a nonlocal sparsity-based prior for typical video sequences. Specifically, authors first extend block matching (nearest neighbor search) into patch clustering (k-nearest-neighbor search), which represents motion in an implicit and distributed fashion. Then authors show how to exploit the sparsity constraint by sorting and packing similar patches, which can be better understood from a manifold perspective. Under the Bayesian framework, authors treat both patch clustering result and unobservable data as latent variables and solve the inference problem via variational EM algorithms. A weighted averaging strategy of fusing diverse inference results from overlapped patches is also developed. The effectiveness of patch-based video models is demonstrated by extensive experimental results on a wide range of video materials.

Xin Li, [7] proposed a patch-based variational Bayesian framework of image processing using the language of factor graphs (FGs). The variable and factor nodes of FGs represent image patches and their clustering relationship respectively. Unlike previous probabilistic graphical models, authors model the structure of FGs by a latent variable, which gives the name "stochastic factor graphs"(SFGs). A sparsity-based prior is enforced to the local distribution functions at factor nodes, which leads to a class of variational expectation-maximization (VEM) algorithms on SFGs. VEM algorithms allow us to infer graph structure along with the target of inference from the observation data. This new framework can systematically exploit nonlocal dependency in natural images as justified by the experimental results in image denoising and inpainting applications.

## IV. PROBLEM IDENTIFICATION

Image inpainting, also known as image completion, is the problem of finding missing parts of an image using only the available content and some regularization constraints. The disoccluded areas should cause few, if any, visual artifacts, which makes inpainting a difficult image processing problem involving knowledge about image models and regularization techniques. While it has been a long time problem for painting restoration, it has gained in importance with the growth of the digital photography market, since it allows users to remove disturbing elements from their pictures or repair damages such as visible dust on the sensor of the camera or scratches in an old digitized photograph.

Traditional approaches to inpainting try to find a good continuation of the surroundings of the holes, effectively propagating lines inside. Hence, these techniques are also known as geometry driven algorithms. Isophote propagation is obtained by solving partial differential equations such as the heat flow of the Navier-Stokes equation. Since this tend to produce blurred estimates, edge-preserving techniques such as Total Variation minimization or curvature motion were used as an alternative. However, these models still lack a support for texture information and are consequently unable to reproduce it. Geometry-based methods can thus hardly be applied to large area inpainting without noticeable visual disturbance.

Since textures, and especially structured ones like brick walls, are hard to model due to their high yet constrained variability, people working in the texture synthesis field successfully applied alternative exemplar-based techniques, which tackle the lack an explicit mathematical texture model. Starting with the work of Efros and Leung, exemplar-based techniques take as input a source image containing the desired texture. Then, random parts of the source are extracted and used to fill the larger target picture, with a special treatment to avoid visual discontinuities between neighboring overlapping patches (see [5] for instance). These techniques were quickly applied to texture inpainting. They are however sensitive to the order in which gaps are filled, which can create disturbing subjective contours. Hence, the authors of [6] defined careful heuristics for choosing which pixels to process first, and managed to successfully inpaint large areas. This type of approach can even be extended to the case of video inpainting.

Few attempts were made however to conciliate geometry-driven and exemplar-based techniques in an unified framework. Simultaneous geometry and texture inpainting algorithms that have so far been proposed, such as the work, separate inpainting in two distinct steps dedicated to geometry diffusion and texture synthesis respectively. This approach requires first the decomposition of the image into a geometric part, or sketch, and a textural part, which is still an arduous task [9]. Specifically, the texture function spaces used contain only very regular oscillating patterns, which is seldom the case for real life textures such as the aforementioned bricks.

Study an extension of to the problem of image inpainting, that we originally proposed. We will start by briefly describing the inpainting problem and the various attempts at solving it, that can be roughly divided in two groups: exemplar-based or diffusion-based. Since graphs can model any kind of inter-data relationship, depending only on the way connections is made, our initial intuition was that they are good candidates to derive both local and non-local regularization frameworks. Then, we detail the Jacobi iterations used to solve the inverse problem in this case. Finally, we comment on some results on both synthetic and real images with an emphasis on large area inpainting, which is currently the most challenging task since relatively simple algorithms can correctly reconstruct images with numerous missing random pixels.

## V. CONCLUSION

Patches have been used successfully for analyzing and synthesizing images and videos. Patches from one part of an image have been stitched together to synthesize new images with similar texture, or to in-paint texture into an interior region. A patch in an image is defined as a set of neighboring values that are presumed to be related because of their close proximity. The concept is the same except that patches take on shape, where two of the dimensions are spatial and the third is time. The reason for the prevalent use of patches is their ability to capture high-order statistics and model short range dependencies in a computationally efficient manner. Soon after that, Wang and Adelson showed that patches could be used for efficient video compression. In related work, “textons” use image patches within a structured mathematical framework, to account for texture using a patch-based representation. In these cases, patches were used primarily for analyzing image data.

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