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IDENTIFYING THE SELECTED IMAGE FROM MULTI LAYERED PATCHES USING IMAGE PROCESSING

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***Abstract*— We propose an image processing model recognize image in multi layered patches. We extract all patches with overlaps, refer to these as coordinates in high-dimensional space, and order them. The generative models can be learned one layer at a time and when learning is complete they have a very fast inference procedure for computing a good approximation to the posterior distribution in all of the hidden layers This enables us to obtain good identity of the selected image by applying relatively simple identifier (1D) operations to the reordered set of pixels. We explore the use of the proposed approach to image denoising and inpainting, and show promising results of natural images.**

***Index Terms*— patch-based processing, pixel permutation, denoising, inpainting**

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1. INTRODUCTION

Image recognition is the process of identifying and detecting an object or a feature in a digital image or video. This concept is used in many applications like systems for factory automation, toll booth monitoring, and security surveillance. Recent days, image processing using multi layered patches has become very popular and was shown to be highly effective to see [1-13] for representative work. The core idea behind these and many other contributions is the same: given the image to be processed, extract all possible patches with overlaps these patches are typically very small compared to the original image size. The processing itself proceeds by operating on these patches and exploiting interrelations between them. Patch-based algorithms are commonly used, knowledge of the properties of fixed size image patches would prove particularly useful and interesting. We are concerned with investigating the overall distribution of vector based patches of general images.

The remainder of the paper is organized as follows. Section 2 previous research. Section 3 ISIMLP method Section 4 presents the comparison's of work 5 mention conclusion.

2. PREVIOUS RESEARCH

In our previous work [14] and [15] we proposed yet another patch-based image processing approach. We constructed an image-adaptive wavelet transform which is tailored to sparsely represent the given image. We used a plain 1D wavelet transform and adapted it to the image by operating on a permuted order of the image pixels1. The permutation we proposed is drawn from a shortest path ordering of the image patches. This way, the patches are leveraged to form a multi scale sparsifying global transform for the image in question. We embark from our earlier work as reported in [14] and [15], adopting the core idea of ordering the patches. However, we discard the globality of the obtained transform, the multi-scale treatment, and the sparsify-driven processing that follows. Thus, we propose a very simple image processing scheme that relies solely on patch reordering. We start by extracting all the patches of size $\sqrt{n} \times \sqrt{n}$ with maximal overlaps. Once these patches are extracted, we disregard their spatial relationships altogether, and seek a new way for organizing them. We propose to refer to these patches as a cloud of vectors/points in Rn, and we order them such that they are chained in the "shortest possible path", essentially solving the traveling salesman problem [16]. This reordering is the one we have used in [14] and [15], but as opposed to our past work, our treatment from this point varies substantially. A key assumption in this work is that proximity between two image patches implies proximity between their center pixels. Therefore if the image mentioned above is of high quality, the new ordering of the patches is expected to induce a highly regular (smooth or at least piece-wise smooth) 1D ordering of the image pixels, being the center of these patches. When the image is deteriorated (noisy, containing missing pixels, etc.), the above ordering is expected to be robust to the distortions, thereby suggesting a reordering of the corrupted pixels to "what should be" a regular signal. Thus, applying relatively simple 1D smoothing operations (such as filtering or interpolation) to the reordered set of pixels should enable good recovery of the clean image.

3. ISIMLP(Identify the selected image from multi layered patches) model

In this model consists binary visible units and hidden units with specified layer ID's. A joint configuration, (v, h) of the visible and hidden units has an pushed up by:

$$E(v,h)=\sum_{i\in visible} bivi-\sum_{j\in hidden} bjhj-\sum_{i,j} b1wij$$

where vi, hj are the binary states of visible unit i and hidden unit j, b_iv_i, bjh_j are their biases and wij is the symmetric weight between them. The network assigns a probability to every possible image via this energy function and the probability of a training image can be raised by adjusting the weights to lower the energy of that image and to raise the energy of similar, reconstructed images that the network would prefer to the real data. Once binary states have been chosen for the hidden units, a reconstruction is produced by setting each vi to 1. The states of the hidden units are then updated once more so that they represent features of the reconstruction.

After that to verify the visible units that will be pick up into selected vector, next compare user selected layer patch layer & location ID's so selected layer patch image will show on canvas or screen

4. COMPARISION's OF THE WORK

A single layer of binary features is usually not the best way to capture the structure in the data. We now show how **ISIMLP'S** can be composed to create much more powerful, multilayer models. The directed connections from the first hidden layer to the visible units in the final, composite graphical model are a consequence of the fact that we keep the p(v|h) but throw away the p(h) defined by the first level RBM. In the final composite model, the only undirected connections are between the top two layers.

5. CONCLUSION

We have proposed a new image processing scheme which is based on smooth 1D ordering of the pixels in the given image. We have shown that using a carefully designed permutation matrices and simple and intuitive 1D operations. The proposed scheme can be used for image denoising and inpainting, where it achieves high quality results. The model with lateral connections is very good at capturing the statistical structure of natural image patches. In future work we hope to exploit this in a number of image processing tasks that require a good prior over image patches..

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