Usableness Improving for the Nonlocal Means Image Denoising Algorithm to Use it on Low-powered Embedded Computing Units

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Abstract

In this note, we propose an approach for rapid nonlocal means image denoising algorithm. The nonlocal means image denoising algorithm is one of the best state-of-the-art denoising methods to lift signal/noise ratio. Noise necessarily appears on photo-registering CCD matrixes during image registering process. Proposed method was first mentioned in 2005 by Buades, Coll, Morel. The native algorithm has fatally high performance complexity, which make it impossible to use it even by a desktop (without video-card using, of course). At the same time, we find the native algorithm some inefficient. We have realized and tested approaches proposed by some papers, have taken excellent results and have to propose new approach which we have in plans to realize in the nearest future.

Index Terms: image processing, nonlocal means image denoising.

I. INTRODUCTION

The image denoising problem is very old. As we all excellent know, there are no high-result methods nowadays: the eternal problem of this yield is how to cut noise off without any useful information damage. Review of denoising methods are presented in work [1] as well as a new one which devoted our work for, so-called nonlocal means image denoising algorithm. This new approach gives state-of-the-art results for the image denoising, decreasing noise level given that saving useful small details and textures on image.

In this method restored gray value of each pixel are defined as weighted sum of all pixels on the image. Each weight is proportional identity between target and source pixels in some local neighbourhood. The basic idea is following: real images have repeating patches AND averaging those patches decreases stochastic component of the image.

In spite of high results quality, detected by using nonlocal means approach, the high native nonlocal means algorithm computational complexity negates its practical application by embedded computing units.

High computational complexity caused by calculating weight coefficients for each image pixel for a whole denoising process. For each processed pixel all image are analized for similar patches. The computational complexity has quadratic dependence of whole image pixels number. There are basic remedy for this problem: to bound similar patches searching by some local neighbourhood (so-called *semi-local denoising*). However, this remedy brings to naught the main advantage of this method – averaging by lot of patches with similar content sufficient to restore textures. So, the nonlocal means image denoising algorithm is not a trivial task and needs for researches.

The nonlocal means image denoising algorithm may be accelerated by the patch preselecting. That approach has described in papers [2,3,4]. We propose an nonlocal means algorithm which is accelerated both by approach from paper [2] and by approach from paper [4].

II. Main part

A. The native nonlocal means algorithm

Nonlocal means image denoising algorithm is a typical smoothing filter. Such filters use averaging by similar pixels in some samples. The assumption of ergodicity we take restored values as weighted sum for all pixels on the initial image (e.g., in case of Gauss smoothing filter the weights are like the gaussian cupola).

Consider the native nonlocal means image denoising algorithm. Lets *v(i)* is an original noised image, where *i* is an index of a pixel. Restored values are weighted sums by the all pixels on the initial image (lets call *I* the set of all pixels on the image):

$$NL(v)(i) = \sum_{j \in I} \omega(i, j) v(j), \tag{1}$$

where $NL(v)(i)$ is a restored value of the pixel with index *i*. Weights are related with an identity between target and source pixels in some neighbourhood:

$$\omega(i, j) = \frac{1}{Z(i)} e^{\frac{-\|v(N_i) - v(N_j)\|_{2,a}^2}{h^2}}, \tag{2}$$

where *Z(i)* is a norm multiplier, $Z(i) = \sum_j w(i, j)$, h is a sensitivity parameter. In expression above $v(N_i)$ is a vector, containing pixels values into neighbourhood of the pixel with index *i*, $v(N_i) \equiv v(j)_{j \in N_i}$, where N_i is a set of neighboring to *i*-th pixels (this set usually is quadratic with beforehand defined size). Vector's norm in the expression (2) is a distance in the euclidean space, weighted by the gaussian with null mean and dispersion *a* [1].

During the image denoising process (native version) for image consisting of *M* pixels we have to compute *M* weight coefficients for each pixel and M^2 weight coefficients to compute at all. To compute each weight coefficient we have to compute weighted euclidean distance between two vectors, whose dimensionality is equal to $4r^2$, where *r* is a radius of our pending neighbourhood for comparisons (N_i). It's a bitter slow algorithm, too slow to use its really on practice.

To solve the high performance problem it's an important task to decrease overall quantity of computing weights by dint of sifting out obviously different patches during denoising process.

B. Patches preselection

All time during any nonlocal means image denoising process spends for the pixel-by-pixel comparison between patches. Obviously, that one what we have to accelerate our nonlocal means image denoising algorithm is patches preselecting. So, our goal is to build graphical database optimized for the nonlocal means image denoising algorithm: time spending by data preparing must be comparable with total time spending by similar patches searching.

C. Statistical preselection

The idea of the patch statistical preselecting is easy. By fast transformation over initial image we could take so statistical features for each patch as mean and dispersion. If two patches have significantly different statistical features, we do not need to futher pixel-by-pixel comparison. In paper [3] authors propose to use mean and dispersion as the same statistical features, whose difference guarantee significant pixel-by-pixel difference. However, in case of non-equidistant noise power (it is typical for real photographies taken by CCD-matrixes), choice to using dispersion as such feature is not absolutelly right. So we prefer to use average gradient direction as the second statistical feature as proposed in [2].

This approach has taken tenfold acceleration for the nonlocal image denoising algorithm in our implementation (it's a bad result, you could take better!).

D. Preselection via trees

Another method proposed in the paper [4]. The authors propose to preselect patches by means of the same distance measure that is used in the pixel-by-pixel comparison. In order to accompolish this, they propose to arrange all image patches in a binary tree (typical it is the kd-tree, see Fig.1 for an illustration).

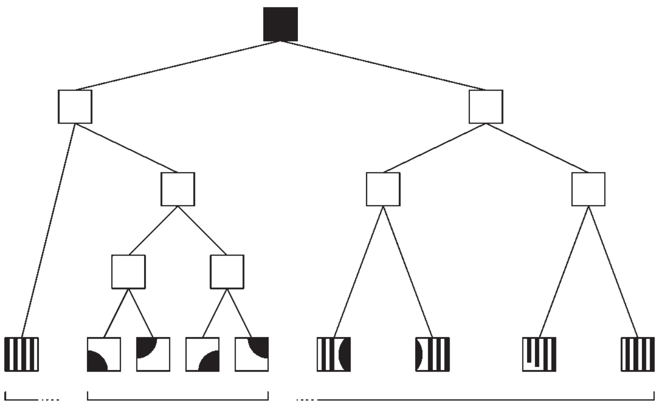

Fig.1. Shcematic illustration of a cluster tree. Leafs contain a relatively small set of similar patches.

Through the use kd-tree our nonlocal image denoiser have taken just 7 minuts for an image with resolution 512x512 points denoising contra 2 hours for the native nonlocal image denoiser. See Fig. 2 for required time to denoise image dependence of the accountable neighbourhood radius.

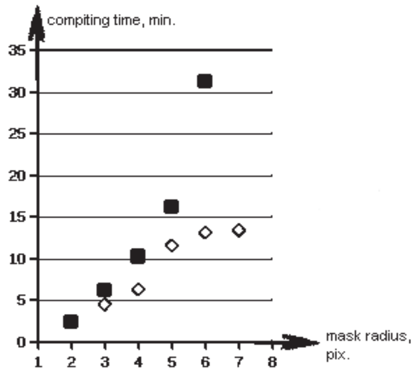

Fig.2. Required time to denoise image dependence of the accountable neighbourhood radius.

Black squares correspond to natime NLM algorithm, hollow rhombus – to tree-accelerated algorithm.

E. Natural photo kd-images features and a new glance for the patch preselection

In kd-space which has dimensionality equaling neighbourhood pixels count we place points with coordinates whic equal respective pixels in the neighbourhood brightness. So in the multidimentional kd-space we get points set which target pixel's brightness is attached by.

We have made natural photos kd-images 2D projections, which are listed below by Fig.3 (logarithmic scale).

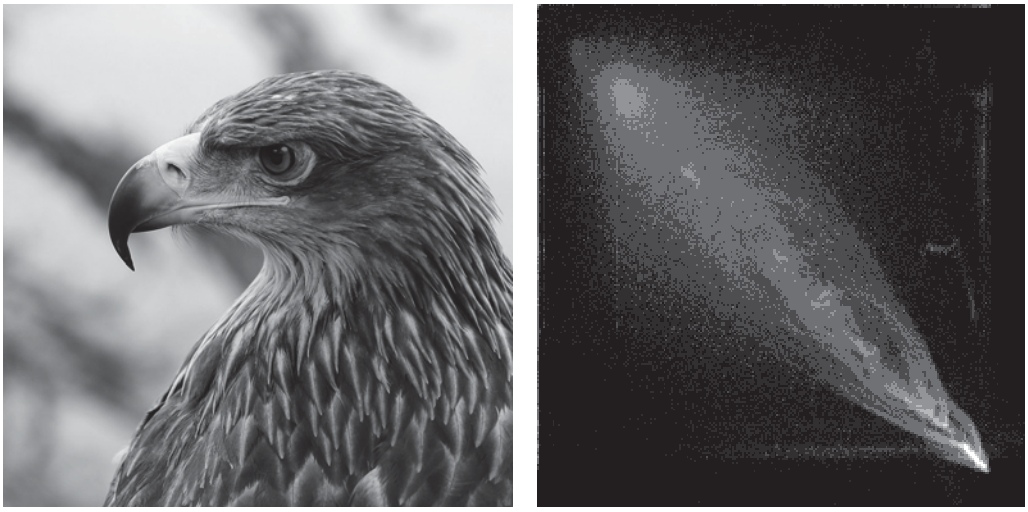

Fig.3. Original image (left) and its kd-image 2D projection on a logarithmic scale (right).

Notice that by the diagonal there are overwhelming majority of the image patches. On the other hand the same diagonal corresponds samples with zero variances and normal for the same diagonal direction corresponds average means for the patches.

So if we rotate whole kd-image 45 degrees and then build kd-tree, we will take kd-tree with statistical preselection inside and faster tree build-searching process. Both the statistical preselecting and the preselecting via binary trees are not optimal. Time spending by data preparing must be comparable with total time spending by similar patches searching. In this way by using 45 degrees rotation we plan decrease needed for nonlocal image denoising algorithm time.

Also we propose first compute kd-image points density with preliminary averaging and then use local averaging in kd-space.

So, we are going to take the significantly accelerated nonlocal means image denoiser. There are many ways to build-using this combined tree. Implementation this is our goal in the further work.

III. Conclusion

On the ground of testing earlier proposes for the nonlocal means image denoising algorithm computational complexity decreasing we have proposed a new approach for the algorithm acceleration. Our approach is just in theory and we plan to relize this and to propose experimental results.

References

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