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# A fast nonlocally centralized sparse representation algorithm for image denoising

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ABSTRACT

The sparsity from self-similarity properties of natural images, which has received significant attention in the image processing community of researchers, is widely applied for image denoising. The recently proposed nonlocally centralized sparse representation (NCSR) algorithm that takes advantage of the sparse representations (SRs) and the nonlocal estimate of sparse coefficients (NESCs) has shown promising results with respect to noise reduction. Despite successful combination of the above two techniques, the iterative dictionary learning and the nonlocal estimate of unknown sparse coefficients make this algorithm computationally demanding, which largely limits its applicability in many applications. To address this problem, a fast version of the NCSR algorithm called FNCSR algorithm, which is based on pre-learned dictionary and adaptive parameter setting approaches, was proposed in this paper. Specifically, we adopted the same dictionary learning approach, i.e, the K-means and principal component analysis (PCA), with the NCSR algorithm to obtain a dictionary for each image in a selected image dataset including high-quality natural and texture images. Then we applied PNSR index to objectively assess the image quality of the reconstructed images using these dictionaries throughout the image dataset. The dictionary providing the best average reconstructed quality was selected as fixed dictionary, i.e., the pre-learned dictionary, for sparse coding throughout the iterative denoising process, which implies that it no longer requires dictionary learning procedure within the framework of the proposed FNCSR algorithm, resulting in greatly decreased execution time. In order to further improve computational efficiency, we employed quality-aware features and support vector regression (SVR) technique to build a fast noise level estimator (NLE) to estimate the noise level from a single noisy image. The parameters related to the NESC, i.e., the search window and the search step, which influences the computational performance of the NCSR algorithm strongly, were chosen automatically according to the estimated noise level. Compared to the original NCSR algorithm, these modifications lead to substantial benefits in computational efficiency (a performance gain of about 90% can be achieved) without sacrificing image quality too much (the largest decline is less than 0.55 dB and 0.014 in terms of PSNR and SSIM indices). Compared with other state-of-the-art denoising algorithms, experimental results show that the proposed FNCNR algorithm also achieves comparable performance in terms of both quantitative measures and visual quality.


## 1. Introduction

The contamination of digital image by noise is more or less introduced during image acquisition or transmission. Aiming to estimate the original image from its noise-corrupted observation while preserving as much as possible the image edges, textures and fine details, image denoising as an important preprocessing step in many image processing and analysis tasks is a fundamental problem in image processing [1–8]. Various image denoising algorithms have been developed in last few decades for the quality improvement of images corrupted with some kind of noise model that is often assumed to be additive white Gaussian noise (AWGN) in the image denoising literature. The reader can refer to [9,10] for a more comprehensive overview of the denoising algorithms. Although image denoising algorithms has been studied for decades, their performances in terms of noise reduction and running time are still not perfect. Most algorithms have not yet attained a desirable level of applicability. The search for efficient image denoising methods is still a valid challenge. In the past decades, there have been many well-known and classical denoising algorithms proposed, such as spatial filter-based approaches [11], partial differential equations [12], wavelet thresholding-based approaches [13–15], total-variation (TV)-based approaches [16,4,5], non-local

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means (NLM)-based approaches [10,1,17,6,18], sparse representation (SR)-based approaches [2,7], etc. Most of the leading denoising algorithms always consist in refinements of and crossings between aforementioned classical algorithms [19]. Among them, algorithms such as BM3D [20,3], centralized sparse representation (CSR) [21] and learned simultaneous sparse coding (LSSC) [22], achieve state-of-the-art denoising performance benefiting from sparse representation that codes an image patch as a linear combination of a few atoms chosen out from an over-complete dictionary. Sparse representation-based denoising algorithms have been proven to have a strong ability to denoise AWGN noise [23], not only because the trained over-complete dictionary has greater robustness in the presence of noise, but also the atoms are of good characteristics such as localized, oriented, and bandpass, which characterize well the features of visual cortex, and thus tend to produce better results that agree with the human visual system (HVS). For this reason, it has been applied to image denoising and successfully acquired great popularity over the years. As a prominent representative, an image denoising algorithm by utilizing the sparse representation of the edges was recently presented by Liu et al. in [2]. Their experimental results show that the algorithm achieves competitive PSNR and SSIM values and retains the image details, especially for images with complicated backgrounds and abundant texture regions. The main advantage of Liu's algorithm lies in the fact that it can capture image details such as edges and represent them with a sparse description effectively.

Generally speaking, the key of sparse representation-based denoising algorithms is to construct or learn an appropriate dictionary that can accurately fit the local structures of images, therefore successful sparse representation-based denoising algorithms depend on the dictionary whose capability is closely related to the performance of sparse coding, and whether it matches the image features [24]. The existing dictionary learning approaches include K-singular value decomposition (K-SVD) [25], locally learned dictionary (KLLD) [26], learned simultaneous sparse coding (LSSC) [22], and principle component analysis (PCA) [7]. These dictionary learning algorithms can work effectively on denoising because in these algorithms, the atoms of the dictionary are always optimized in an iterative scheme such that the representation of the training images on the dictionary can be specified as sparse as possible. For instance, the most well-known KSVD algorithm adopts an iterative procedure and contains the time-consuming singular value decomposition (SVD). The required CPU time for the dictionary learning for a normal problem is very high (about some minutes or more), which hinders its application in large-scale images. In short, although dictionary learning has been intensively studied, how to efficiently utilize it in the denoising algorithm is still a challenging task.

Recently, Dong et al. combined the ideas of sparse representation and non-local self-similarity of image patches within a given image, and proposed a so-called nonlocally centralized sparse representation (NCSR) algorithm [7] with very powerful denoising performance for Gaussian noise (GN). The combination of sparse representation (dictionary learning) and non-local similarity formes a prospective research interest. It has become increasingly recognized as providing extremely high performance for image denoising in terms of noise reduction. However, it has a very high computational complexity. Specifically, in the NCSR algorithm, K-means and PCA are applied to image patches extracted from the corrupted image itself or the denoised intermediate image to learn a temporary dictionary. The patches are clustered into $K$ clusters, and a PCA sub-dictionary is learned for each cluster. Then for a given patch, one compact PCA sub-dictionary is adaptively selected to code it, leading to a more stable and sparser representation, and consequently better image denoising results. As we know, K-means and PCA are time-consuming processes, which is one of the reasons for low efficiency of the NCSR algorithm; another reason is that the non-local estimate of sparse coefficients (NESC) is strictly dependent on patch matching, which is also a time-consuming calculation process for finding sufficiently similar patches. Thus, the net effect is that, while the NCSR algorithm is excellent in terms of noise reduction, it is computationally expensive and ultimately limited in large-scale images with increasing complexity.

The contribution of this paper is two-fold. Two improvements (modifications) over the original NCSR algorithm that lead to computational complexity decrease were proposed so that it can potentially be used in time-constrained applications. Specifically, the first improvement is to utilize pre-learned dictionary trained offline from some selected high-quality natural and texture images instead of the dictionary obtained runtime from the given corrupted image itself or the denoised intermediate image so that computational complexity regarding dictionary learning is almost reduced to zero. This is motivated by the fact that the image quality of the reconstructed images with the pre-learned dictionary is satisfactory. Using these, we demonstrate that the proposed approach adopting the pre-learned dictionary can be implemented efficiently; the second improvement relates to the NESC, which is based on the natural redundancy of patterns within natural images and consists in some kind of averaging process carried on similar patches in an image to be denoised. Currently, some internal parameters related to the NESC, such as search window and search step, which strongly influence the computational performance of the NESC, are set fixedly without considering the noise level. In fact, these parameters need to be set according to the noise level to yield good results with respect to noise reduction and computational efficiency. In general, the choice of such parameters is made empirically with trial and error, i.e., manual parameter tuning, and it is difficult to obtain an accurate estimate of the noise level manually. The manual parameter tuning approach is impractical for most denoising applications due to time consuming process. So far it still remains a challenge to accurately estimate the noise level for a variety of input images, especially for those with rich textures [27]. Therefore, a robust and automatic noise level estimator (NLE) is highly demanded, which can consistently estimate noise level with ground-truth value, given only a single observed noisy image. Regarding general approaches to the design and construction of an NLE, refer to Section 3 for details. In this paper, we proposed a new fast NLE based on the quality-aware features and learning framework, which is used to automatically set the parameters of the NESC and effectively reduce the computational complexity of pairwise distances between the similar patches. Compared with other NLEs, the proposed NLE deploys a quite different strategy, which reacts reasonably to noise, is easy to implement, and works efficiently.

In general, both noise reduction and computational efficiency are two important evaluation indicators of denoising performance. In fact, they are also conflicting prerequisite for comprehensive analysis of denoising algorithm. That is, most of the denoising applications require a trade off between the noise reduction and computational cost. The major goal of this paper is to investigate the feasibility of reducing the computational complexity of the dictionary learning and the NESC, which are two of the most time-consuming modules in the NCSR algorithm. Extensive experimental results show that, our proposed fast NCSR (FNCSR) algorithm adopting two technical improvements can achieve a very competitive performance regarding the noise reduction and the computational complexity, compared to its naive implementation and other state-of-the-art denoising algorithms. To the best of our knowledge, this has not been done so far in the literature.

The rest of the paper is organized as follows. In Section 2, the NCSR denoising algorithm is briefly reviewed. The proposed