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Fingerprint denoising using ridge orientation based clustered dictionaries

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ABSTRACT

In this paper, we introduce a novel approach of fingerprint denoising using ridge orientation based clustered sub dictionaries. The idea behind this approach is to group the patches of similar geometric structures or dominant orientation and construct separate sub-dictionaries for each group. The orientation of ridge or a valley has been exploited in finger print matching algorithms in the past. In the proposed method, the same concept of ridge orientation is utilized to group the patches and to subdivide a large dictionary into array of sub dictionaries. The new approach undergoes three steps i.e. *ridge orientation based clustering*, *dictionary learning* and *sparse coefficient calculation*. While reconstructing the image in final step, the minimum residual error criterion is used for choosing sub dictionary for a particular patch. The algorithm performance is experimentally compared with other existing methods not only in terms of PSNR, SSIM measures but also in terms of Euclidean distance parameter, which is used, for fingerprint matching procedures. The simulation results demonstrates that the new method achieves better results in comparison with its counterparts and will establish in improving performances of fingerprint-identification systems.

1. Introduction

Automatic fingerprint identification systems (AFIS) are integral part of man machine interface systems for verification of individual's identity. Fingerprints has proved to be an effective biometric identifier and extensively utilized in forensic science for criminal investigations [1] and in biometric identification devices for civilian as well as commercial applications [2]. Efficiency of fingerprint recognition systems is largely dependent on the input fingerprint image quality [3]. There could be various factors behind the substandard quality of fingerprint images, such as performance of the image acquisition sensor, image corruption with noise due to variation in skin and impression condition and so on. Probability of error in the recognition process can be reduced by quality improvement through image denoising.

Image denoising is a challenging problem and has acquired considerable interest of researchers from both academia and industry. The classic image denoising problem is modeled by assuming an ideal image X being captured in the presence of an additive zero-mean white and homogeneous Gaussian noise with standard deviation σ. The captured image Y is represented by,

$$Y = X + n(\sigma^2) \qquad (1)$$

There are numerous denoising algorithms [4–9] present in literature to estimate X from Y. Here we are focusing towards one specific approach i.e. sparsity based image denoising. Elad and Aharon [10] addressed image denoising problem using K-SVD algorithm [11] of optimal overcomplete dictionary construction. In this method each patch is denoised by representing each patch as a linear combination of only few atoms in the dictionary. Mairal et al. [12] proposed multiscale global dictionaries for performance improvement of dictionary learning. Chatterjee and Milanfar [13] proposed locally learned dictionaries (K-LLD) for image denoising, which performs clustering based on similar geometric structures and employs local weight functions as features. Xiaoqiang et al. [14] proposed a Bayesian-based sparse coding algorithm, which employs spike and slab prior to provide accurate prediction and effective sparse representation. Zhang et al. [15] introduced a new approach of image denoising, which creates 2D dictionary based on the self-similarity inherent in the images. This method relies on idea that if group of similar patches are assembled in matrix form, then there exist linear correlations among both columns and rows. Yang et al. [16] proposed new dictionary learning for image noise reduction, which exploits structural similarities of image. Dabov et al. [17] proposed a state-of-art method, which yields excellent

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PSNR performance. BM3D algorithm is a unified framework of dictionary learning and structural clustering.

The problem of fingerprint denoising is peculiar in nature and need special methods for denoising. In this paper, we propose a novel framework for denoising fingerprint images. Instead of having a single dictionary, the proposed method clusters the training patches into groups based on dominant orientation of patch. Authors believe that use of sub dictionaries based on dominant orientation best describe the underlying image data and improves the effectiveness of sparse modeling of information in a fingerprint image in form of local ridge patterns. Atoms from sub dictionary with minimum residual error are used during reconstruction of patches.

The rest of this paper is organized as follows: in Section 2, the sparse reconstruction model is depicted. Section 3 describes the proposed fingerprint denoising algorithm. In Section 4, experimental results are presented to evaluate the performance and demonstrate the effectiveness of our proposed method. Finally, conclusions are presented in Section 5.

2. Sparse reconstruction model

The concept of sparse based image denoising is motivated from the idea that a high quality image X can be approximately coded as a linear combination of few columns (atoms) of an over complete dictionary. Overcomplete dictionaries contains more atoms than the dimension of the signal. A signal $X=\{x_1, x_2\ldots.., x_n\}$ is said to be sparse when very few of entries x_i possess non-zero values. Sparse representation computes the summation of the constituent atoms weighted with their sparse coefficients vector. However, computing such sparse codes within overcomplete dictionaries is non-trivial, in particular because the decomposition of an image in terms of atoms of an overcomplete dictionary is not unique. Processing the whole image as a large vector is numerically cumbersome, Elad & Aharon (2006) [10], proposed breaking down the image into smaller patches and learning a dictionary of patch-sized atoms. Handling high dimensionality of data in image denoising is major challenge, the patch based method models the patches with relatively lower dimension, seems the effective solution to tackle this problem.

Given an image observation patch of size $\sqrt{p} \times \sqrt{p}$ ordered lexicographically as column vector $x \in R^p$ and a sparsifying dictionary $\varphi=\{\varphi_1, \varphi_2\ldots.., \varphi_c\} \in R^{p*M}$ (the columns $\varphi_i \in R^p$ represent the atoms), sparse representation refer to finding a coefficient vector $\alpha \in R^M$ in the domain spanned by the dictionary φ while synthesizing following equation:

$$\hat{\alpha} \in \text{argmin}_\alpha ||\alpha||_0 \text{ subject to } x=\varphi\alpha \quad (2)$$

The solution is indeed very sparse where $\|\hat{\alpha}\|_0 < < M$. While synthesizing approximately, the equality constraint in Eq. (2) can be replaced by a l_2 norm inequality constraint.

$$\hat{\alpha} \in \text{argmin}_\alpha ||\alpha||_0 \text{ subject to} ||x-\varphi\alpha||_2 \le \varepsilon_1 \quad (3)$$

where ε controls the misfitting between observed and recovered signal $\hat{x}=\varphi\hat{\alpha}$. Now considering a patch y, noisy version of x, contaminated with additive white Gaussian noise. The denoising of noisy patch y can be formulated as following optimization problem.

$$\hat{\alpha} \in \text{argmin}_\alpha ||\alpha||_0 \text{ subject to } ||y-\varphi\alpha||_2^2 \le \varepsilon_2 \quad (4)$$

The denoised patch can be recovered as $\hat{x}=\varphi\hat{\alpha}$. The optimization problem in Eq. (4) can also be reformulated in its unconstrained penalized form.

$$\hat{\alpha}=\text{argmin}_\alpha ||y-\varphi\alpha||_2^2+\beta||\alpha||_0 \quad (5)$$

The solution of Eq. (5) is NP hard problem; however, l_1-norm can be used to make it computationally tractable (convex) as an alternate to l_0-norm (non-convex). Matching pursuit class of algorithms that include orthogonal matching pursuit (OMP), basis pursuit (BP) and gradient pursuit (GP) provide efficient and computationally tractable solutions to the optimization problem.

3. Proposed method

3.1. Sparse based denoising framework

The sparse based denoising framework comprises of restoring true image X from its noisy version Y contaminated with additive white Gaussian noise. The task involves suitable dictionary learning and coefficient calculation for efficient sparse representation of denoised image X. Elad and Aharon [10] proposed an image-denoising

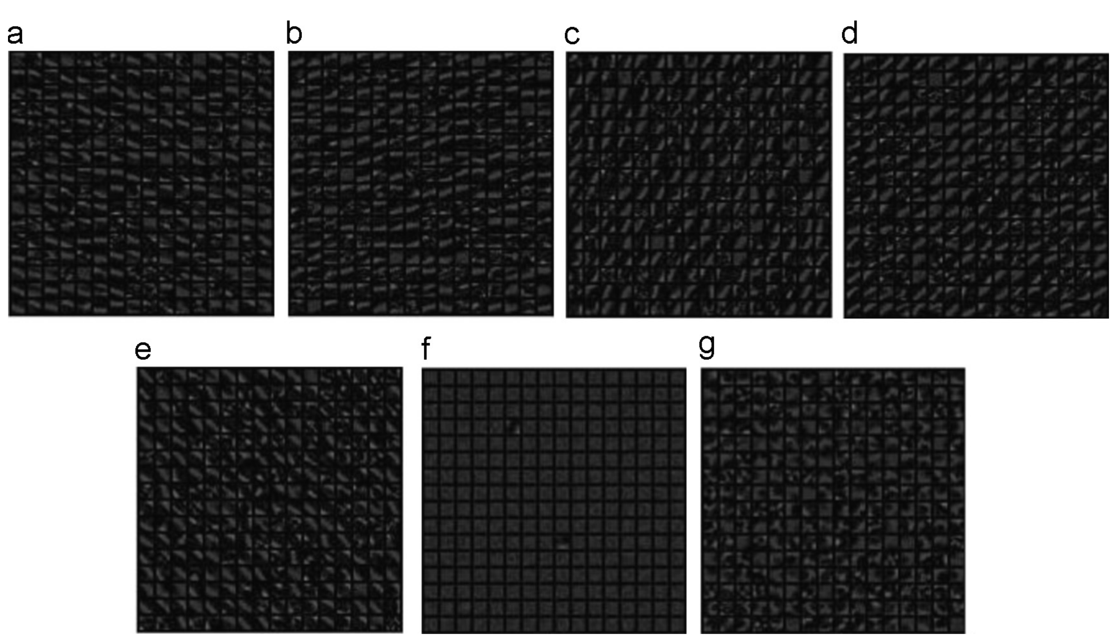

Fig. 1. Ridge orientation based clustered sub dictionaries (a)–(e) dominant orientation, (f) smooth and (g) non-dominant orientation.