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Research article

A novel dictionary learning-based approach for Ultrasound Elastography denoising

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Abstract: Ultrasound Elastography is a late-model Ultrasound imaging technique mainly used to diagnose tumors and diffusion diseases that can't be detected by traditional Ultrasound imaging. However, artifact noise, speckle noise, low contrast and low signal-to-noise ratio in images make disease diagnosing a challenging task. Medical images denoising, as the first step in the follow-up processing of medical images, has been concerned by many people. With the widespread use of deep learning technique in the research field, dictionary learning method are once again receiving attention. Dictionary learning, as a traditional machine learning method, requires less sample size, has high training efficiency, and can describe images well. In this work, we present a novel strategy based on K-clustering with singular value decomposition (K-SVD) and principal component analysis (PCA) to reduce noise in Ultrasound Elastography images. At this stage of dictionary training, we implement a PCA method to transform the way dictionary atoms are updated in K-SVD. Finally, we reconstructed the image based on the dictionary atoms and sparse coefficients to obtain the denoised image. We applied the presented method on datasets of clinical Ultrasound Elastography images of lung cancer from Nanjing First Hospital, and compared the results of the presented method and the original method. The experimental results of subjective and objective evaluation demonstrated that presented approach reached a satisfactory denoising effect and this research provides a new technical reference for computer aided diagnosis.

Keywords: dictionary learning; K-SVD; denoising; PCA; Ultrasound Elastography

1. Introduction

Elasticity is a physical parameter that corresponds to the expression of the doctor's tactile sensation in clinical diagnosis. However, determing the softness and hardness of the tissue by palpation is subjective, and powerless to the size and depth of the tissue. The advent of Ultrasound Elastography can provide physicians with information about tissue elasticity, offering a new way to diagnose disease. In the process of medical imaging diagnosis, the requirements for imaging quality are very high; lower image quality would affect the diagnosis of diseases. The noise in traditional Ultrasound images is often dominated by speckle noise. However, because the imaging mechanism of Ultrasound Elastography is different from that of conventional Ultrasound imaging, the noise generated by Ultrasound Elastography mainly comes from the motion artifacts after compression and deformation of tissue [1]. We generally believe that these noises in the ultrasonic image have a negative impact on the image recognition. Although there are many studies on medical images denoising, many common smoothing algorithms lead to blurred images or edge distortion. Therefore, seeking an algorithm that preserves edge information and removes image noise has always been the aim of scientific research. The ideal denoising results are necessary preprocessing for subsequent segmentation, extraction, recognition, etc. At present, in the field of image processing with a focus on deep learning, we classify denoising methods mainly into deep learning-based denoising methods and other traditional denoising methods. He et al. [2] proposed a deep learning-based joint-filtering-framework. This work consists of a pre-training network and fine-tuning the last two convolution layers of the network. Likewise, Liu et al. [3] proposed an innovative GA-based method to construct CNN structures for medical image analysis automatically. Krull et al. [4], Green et al. [5], Tao et al. [6], and Wu et al. [7] all adopted the deep neural network as the main network combined with prior information, structural information, etc. to construct various denoising models.

However, deep learning methods have their own limitations; they either only be used in specific environments or require large and standard dataset labels, while traditional methods are completely different. In recent years, more and more research scholars have turned their attention to the field of traditional methods. Traditional denoising methods include spatial domain filtering methods, variational denoising methods, no-local regularization, sparse representation etc. Wavelets denoising techniques were demonstrated the usefulness of wavelet denoising for visual enhancement of images by Ouahabi [8,9], but not suitable for high intensity noise. Jomaa et al. [10] proposed a new framework of noise reduction in dynamic PET sequences of small animal heart-based procedures on multi-scale and non-local means methods; these methods take into consideration temporal correlations between images. Gupta et al. [11] combined two conventional filters, i.e., non-local mean filter and bilateral filter into an improved non-local mean filter for suppression of speckle noise in Ultrasound images. Also, Baselice et al. [12] used a statistical criterion based on the Kolmogorov-Smirnov distance for detecting similar pixels across the image. Xu et al. [13] employed a PDE algorithm to depict the local self-similarity of images. On the basis of a nonlinear, spatial, fractional, anisotropic diffusion equation, Wang et al. [14] proposed a feature-preserving, fractional PDE algorithm. In addition, some studies integrate denoising into other image processing stages and comprehensively consider noise suppression [15–17].

Unlike the above methods, sparse representation is using the linear combination of elements in the dictionary to represent the test sample. To address this problem, Valiollahzadeh et al. [18] oversaw a local approach into the account and split the noisy observed image into several blocks; a learning dictionary was used over these blocks and to find the best possible sparse representation of each block with this dictionary. Shahdoosti et al. [19] presented an approach based on compressive sensing and sparse and redundant representations over trained dictionaries. Haq et al. [20] considered and implemented two versions with different adaptation steps for the shape parameter: Half-Adapt and Mean-Norm in the dictionary denoising approach. Nasser et al. [21] presented a novel model for detecting cells based on a sparse representation model, which achieved good results. Furthermore, based on the signal properties of images, the compressing sensing method widespread used in communication area is also applied in image denosing. The primary principle of compressing sensing denoising is to represent signal sparsely to deduct noise by reconstruct images, similar to the dictionary learning techniques presented in this paper by Haneche et al. [22] and Mahdaoui et al. [23]. The artifact noise in Ultrasound Elastography images has an obvious negative impact on disease diagnosis, and there are fewer methods suitable for such denoising. Therefore, this paper focuses on the construction of a sparse dictionary based on dictionary learning methods to eliminate outliers, and avoid destructing useful information such as target edges while removing noise. On the basis of the previous work, we combined the PCA algorithm [24] to make some improvements to the dictionary learning algorithm, which improves the update method of dictionary atoms and provides new options for denoising methods in the future work.

The rest of the paper is organized as follows. The methodology consists of the outline of the presented work; sparse model and sparse dictionary with PCA denoising models are presented in Section 2. The experimental results and analysis are shown in Section 3. Finally, the summary and prospect are exposited in Section 4.

2. Materials and methods

2.1. Overview of this method

In this paper, sparse dictionary learning method is used for Ultrasound Elastography images denoising. Sparse representation of images is particularly popular in the field of image feature extraction, which regards the image as a collection of various image blocks and obtains the key image features of the image through feature extraction. Like this, the principle of dictionary learning-based image denoising is to construct dictionary atom of the training image using the feature that noise has a small component and high frequency in the image, and recover the image information using sparse coefficients to remove noise.

The presented sparse dictionary method is implemented as described by Nasser et al. [21]; we replace the K-SVD method with the feature vectors corresponding to the Max-Eigen of PCA to update the dictionary atoms and the specific stages are described below. Firstly, the denoised image as input is partitioned into a number of overlapping patches, which are represented as sparse linear combinations in the dictionary. The next key problem is to find the representation of the dictionary and the corresponding sparse coefficients to represent the image. At the dictionary training stage, we adopt the PCA method to improve the update speed of dictionary atoms. Finally, the estimated images are reconstructed by combining the sparse dictionary and sparse coefficients to obtain the denoising result. The dictionary learning-based denoised method is summarized in Figure 1.

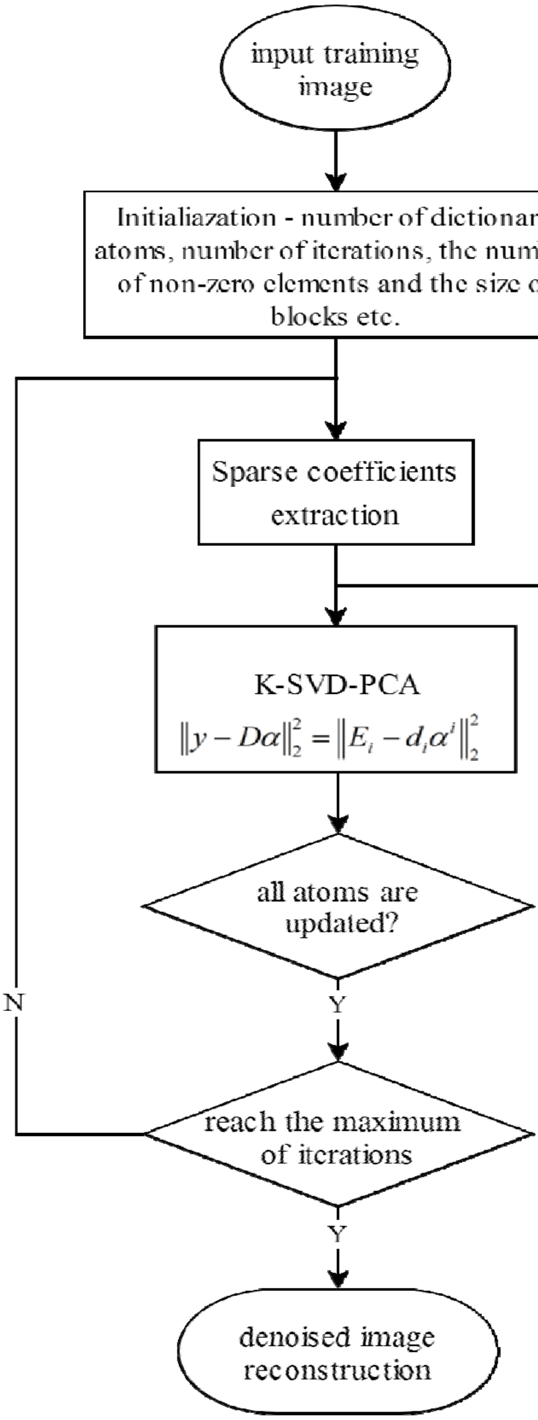

Figure 1. Flowchart of the presented approach.

2.2. Sparse representations about images

Sparse representation is a concept in the field of signal processing, and we often use concepts and methods from the field of signal processing, where the generation, storage, and transmission of an image are often accompanied by high-frequency noise. The existence of noise as a high-frequency component has always been a problem that plagues images. Taking the advantage of the signal sparsity, we can conduct specific processing on the image to separate its high-frequency information from low-frequency information. Since the amount of noise information is small and high-frequency information tends to zero, the high-frequency information is discarded as noise information, and the denoised image is obtained by recovering the low-frequency information, where the process of recovering the image using sparse coefficients is called reconstruction.

We represent the image model with noise as follows:

$$y = x + n \tag{1}$$

where *n* denotes the noise that we try to extract from the noised image *y* to obtain the target image *x*. Assuming there is a certain dictionary *D* and a series of sparse coefficients α, we can use it to restore the image *x*, which is expressed as follows:

$$x = D\alpha \tag{2}$$

where $D \in R^{m\times n}$, if $n > m$, which means *D* is an overcomplete dictionary, each column represents an atom, and the next problem becomes how to find a coefficient matrix *α*. Then, the image *x* is represented by *Dα*. We want α to be as sparse as possible, i.e., there are as few non-zero elements in the matrix as possible. Therefore, $\|\alpha\|_0^0$ should be minimized, thus

$$\min\|y - D\alpha\|_2^2 < \varepsilon^2 \qquad s.t.\ \|\alpha\|_0^0 < L \tag{3}$$

where, ε is the error between the original image and its sparse representation, and $\alpha_i \in R^n$ is the presentation vector. *L* is a predetermined sparse coefficient threshold.

2.3. Dictionary learning

At the image processing stage, to obtain the dictionary *D*, we segment original image into multiple overlapping image patches with size of $\sqrt{m}\times\sqrt{m}$, where patches overlap one pixel with each other. Then we arrange patches like a dictionary into column vectors *x*, $x_i = R^m$, where *i* indicates a vector of the *i-th* column in the image. The image is represented as a linear sparse combination of multiple atoms according to the given Eq (3). The ultimate result indicates that Dα is approximately equal to *x*.

There are many strategies to solve the above problems, such as the notable MP algorithm and OMP (orthogonal matching pursuit algorithm) algorithm, using l0–norm minimization, and BP algorithm, using 1–norm minimization to optimize the model. In order to solve Eq (3), *D* is assumed to be fixed and the sparse matrix is obtained using the OMP algorithm. For dictionary training, in addition to initialization operations such as initializing the required dictionary patch size and initializing the overlap step size, iterative updates are required for each dictionary. K-SVD is an update dictionary selection based on a K-cluster standard for unsupervised learning. $[d_1, d_2 ... d_n]$ and $[\alpha_1, \alpha_2 ... \alpha_m]$ are acquired by training $y_1, y_2 ... y_m$.

Dictionary learning-based denoising algorithm in detail:

1. Dictionary initialization. Initialize the number of dictionary atoms, the number of iterations, the number of non-zero elements, and the size of blocks etc.
2. Sparse coefficients extraction. Based on the dictionary initialization and training dataset, the OMP algorithm is applied to obtain a sparse coefficient matrix α.
3. Dictionary training and update dictionary atoms. Update the objective function as follows,
   for *I* = *1*, *2*,…., *n*
   $\|y - D\alpha\|_2^2 = \|E_i - d_i\alpha^i\|_2^2$, where E_i denotes error matrix.
   The *i-th* atom in the dictionary is updated column by column.
4. Reconstruct the denoised image.

Next, at the reconstruction stage, we reconstruct the denoised image using the dictionary and sparse coefficients obtained from the training to obtain the final pure image.

$$\lambda\|x - y\|_2^2 + \|x - D\alpha\|_2^2 \quad s.t. \quad \|\alpha\|_0 \le L \tag{4}$$

where λ denotes regularization coefficients.

2.4. Dictionary learning denoising with PCA

The K-SVD method is a singular value decomposition of the error and updates the sparse coefficient matrix with the maximum singular value. This process is an approximate reduction of the error term. However, the error between the approximated error and the true error still exists. The inaccurate estimation of the error affects the extraction of the dictionary and the extraction of sparse coefficients. Therefore, we introduce the powerful feature extraction capability of PCA into the K-SVD algorithm and combine dictionary extraction and feature extraction to obtain the optimal dictionary and sparse coefficients matrix of the noising image. Our specific approach is to use the PCA algorithm to extract the feature of the error term, and the maximum eigenvalue is used as the basis for updating the dictionary atoms. We decentralize the error matrix E_i, calculate the covariance matrix of the error matrix, solve the eigenvalues and corresponding eigenvectors of the error matrix, and then take the eigenvector corresponding to the largest eigenvalue to update the dictionary atom. This is shown in the following:

$$E_{\mathrm{i}}(E_i)^T = P\Lambda P^T \tag{5}$$

where P denotes the principle matrix, T represents the "transpose" operator, and Λ denotes eigenvalue value.

3. Results

3.1. Datasets

To address the problem of artifact noise inherent in Ultrasound Elastography, we focused on applying the presented approach in this paper to Ultrasound Elastography image denoising, where only a few strategies are applied to this type of medical image. The presented method has been evaluated on 233 datasets of Ultrasound Elastography of lung cancer with pressure index of 3 provided by Nanjing First Hospital; each sample provides images from different regions and different perspectives. The overall size of the Ultrasound Elastography image is 580 × 500 around. In order to improve the computational efficiency, we pre-segment each dataset to remove most of the background information from the original datasets.

3.2. The experimental results

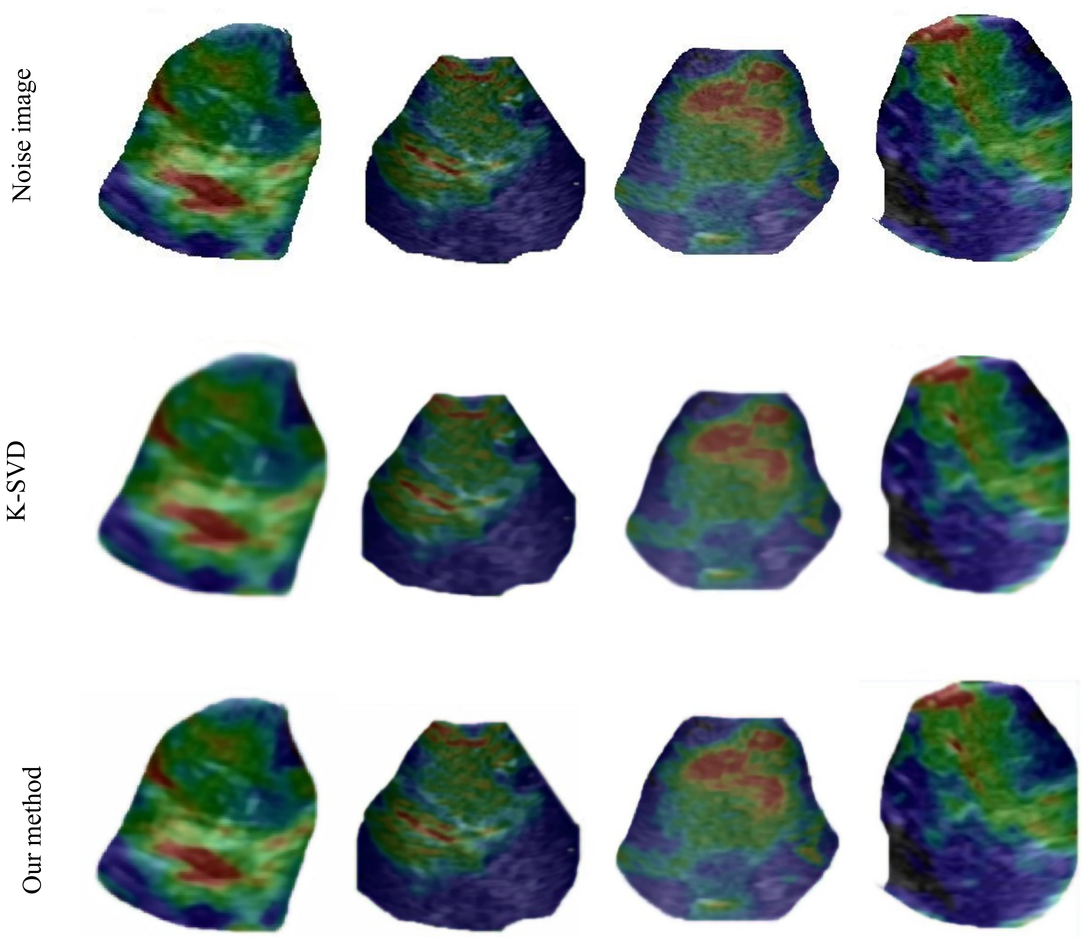

Figure 2. A comparison of denoising result between the K-SVD method and our presented method in lung cancer dataset. The first row represents the original noise image, the second row shows the denoised result obtained by the K-SVD algorithm, and the third row expresses the denoising result obtained by the method proposed in this paper.

In this project, the algorithm is developed based on matlab (matlab 2018b) and runs successfully in a Windows system (Inter core i7, 3.07 Hz and 32 GB RAM). In the experiment, after the dictionary is initialized and the dictionary is trained using the revised method, the sparse representation dictionary can represent the image block expressed on the dictionary atoms. On the basis of multiple experiments, we initialize the dictionary with number of iterations of 20, and a blocksize of 15 × 15. Different iterations, patch size, and dictionary size will have a specific impact on the denoising results.

After repeated verifications in this experiment, the denoised results can satisfy the needs of clinical localization and observation of lesions, and the denoised results of the improved method have been improved to some extent in clinical observation. The results and comparison are shown in the following Figure 2, where the left column represents the original noise images, the middle column shows the denoised results obtained by the K-SVD algorithm, and the right column expresses the denoised results obtained by the method proposed in this paper.

To quantify the denoising results using the proposed strategy, we randomly selected 10 images from the dataset and added different levels of Gaussian noise to them. The following Figure 3 illustrates the results of noise addition and denoised results using our Ultrasound Elastography denoising model, from a macroscopic point of view, our method is effective in removing noise. Figure 4 shows the transformation of SNR improved after 1500 iterations by using the presented method. Experimental results reveal that our denoising model not only satisfy the application in both objective evaluation and subjective evaluation.

Results the method of dictionary learning-based denoising has been evaluated performed well with the scientific combination of both subjective evaluation and the objective evaluation.

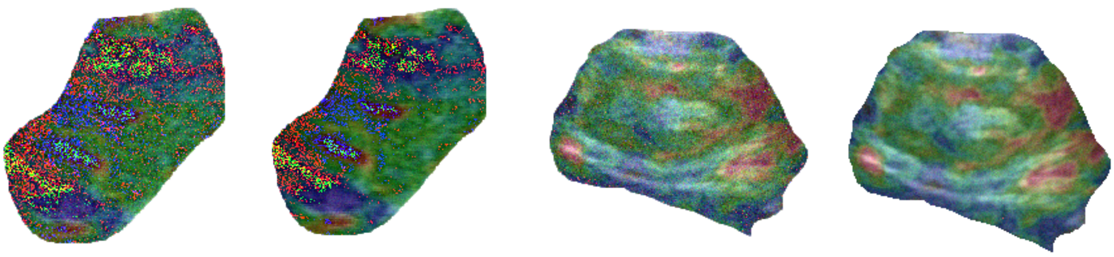

Figure 3. Image added artificially and denoised results.

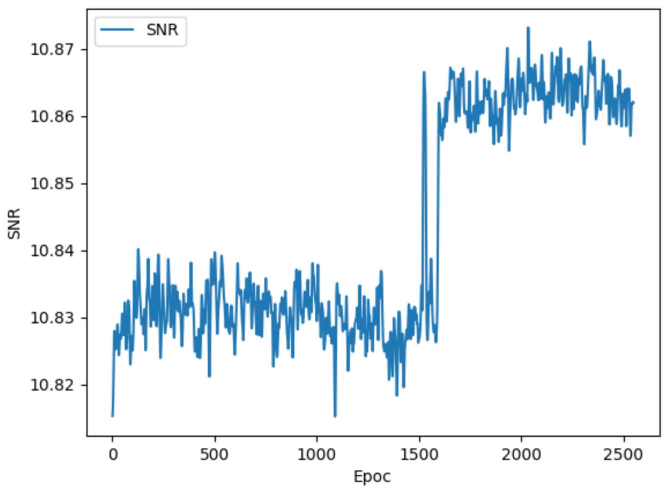

Figure 4. Variation of SNR.

4. Conclusions and discussion

According to the principle of ultrasonic Elastography, when the equipment acquires data such as elastic coefficient and displacement within tissues, there will be a certain amount of noise inherent in elastography due to the limitations of its own equipment and impurities in the ultrasonic echo signal. The existence of these noises will affect the image quality and interfere with the judgment of clinicians and radiologists on the lesion tissue. For the reason that Ultrasound Elastography is a novel imaging technique, there are fewer studies on the denoising of such images. In terms of clinical application, we abandoned deep learning techniques that require large datasets using lightweight algorithms in clinical applications, although deep learning is prevalent indeed. We adopt the traditional feature extraction method of sparse dictionary representation by dividing the image into a number of overlapping patches in a specific size; the Ultrasound elasticity image is trained to obtain the dictionary atoms and sparse coefficients. In the whole process, the PCA method is utilized to improve how the dictionary atoms in K-SVD are updated, and finally the image is reconstructed according to the dictionary and sparse coefficients obtained through training the denoised image. Throughout the process, the PCA method is implemented to improve the updating of dictionary atoms in K-SVD. Ultimately, the image is reconstructed based on the dictionary and sparse coefficients obtained from the training to obtain the denoised image. By analyzing our denoised results attentively, clinicians have given positive evaluation on a certain degree of Ultrasound Elastography quality improvement. From a technical standpoint, the method presented in this paper provides an alternative preprocessing method for subsequent image analysis such as lesion extraction or lesion identification.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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