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Technique for image de-noising based on non-subsampled shearlet transform and improved intuitionistic fuzzy entropy

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ABSTRACT

To overcome the problem of image de-noising, a novel technique based on non-subsampled shearlet transform (NSST) and intuitionistic fuzzy entropy (IFE) is proposed in this paper. Firstly, as a recently developed geometric analysis tool, NSST is utilized to decompose the noised image into multi-scale and multi-directional sub-band images. Secondly, the basic model of intuitionistic fuzzy entropy (IFE) is updated to be an improved IFE, with which each pixel in the noised image is adaptively defined by a pair of membership degree and non-membership degree, and each pixel's weight value can be figured out via improved IFE. Thirdly, the final de-noising image can be obtained by using inverse NSST. Besides, the algorithm for image de-noising is devised and concrete steps are also given. By following the above steps, the noising pixels in the image can be filtered well. Moreover, experimental results indicate that the technique is much more effective compared with other traditional filter ones.

1. Introduction

With the increasing development of the imaging technology [1], the imaging system has been widely applied in the military and civilian areas such as precise guidance [2–4] and target detection [5–9]. The imaging technology plays a very important role in the above fields because of its remarked advantages in invisibility, anti-interfering and far action distance. However, in the courses of the imaging, digitization and transmission, one tough problem which is difficult to settle is the frequent presence of impulse noises, and it often leads to the degeneration of the visual quality. As a result, carrying out image de-noising to restrain the impulse noise is deserved and necessary.

To overcome the above problem, a great many of algorithms have been proposed and developed in the past several years. The effect of traditional linear filters such as the average filter is bad. The anti-noise performance of the traditional median filter greatly depends upon the size of the filter window. Usually, the larger the window size is, the better the filtering performance is. Unfortunately, another problem we have to confront is that the amount of the image detail information and the computational costs will both take a turn for the worse with the window size increasing. Wang and Zhang [10] proposed a modified filtering algorithm called switching median filter (SMF). SMF firstly classifies the pixels into signal points and noisy ones by a noise classification, and then the course of the further filter smooth disposal is carried out by the iterative algorithm. Unfortunately, once the density of impulse noises is relatively thick, the performance of the algorithm will deteriorate. More active and helpful efforts to improve the median filter [11,12] performance are exerted, including adaptive median filter, multi-degree median filter, etc., but on applied occasions, certain limitations always emerge, namely, good performance of the above algorithm do not always exist. Recently, as a significant extension of the theory of fuzzy set (FS), the theory of intuitionistic fuzzy set (IFS) [13] attracts the attention of more and more experts because of its singular superiorities in dealing with uncertainty issues, based on which the theory of intuitionistic fuzzy entropy (IFE) proposed in [14] has also provided us with new thought in measuring the extent of uncertain information.

On the other hand, another type of main-streamed typical tools for image de-noising is based on the multi-resolution geometric analysis which has been widely utilized, and a variety of transformation models have been developed. Reference [15] proposed a novel wavelet-based technique for medical image de-noising. Wu et al. [16] devised a curvelet-based nonlocal means algorithm for image de-noising, and experimental results indicate its good performance. Pogam [17] developed a new image de-noising technique combining the superiorities of both wavelets and curvelets. Compared with previous multi-resolution analysis tools, non-subsampled contourlet transform (NSCT) not only settles the problem that higher-dimensional singularities cannot be efficiently

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represented, but owns the property of shift-invariance. Large constructive work was done by Wang and his colleagues [18]. Besides, the theories of principal component analysis [19] and compressive sensing [20] have been also utilized to settle the problem of image de-noising. However, although the above algorithms enhanced the performance of image de-noising a lot, there are still two aspects which have not been well dealt with. The first one is the effects that some noisy points still exist in the final image. The other is the computational costs. NSCT is a very good tool to deal with the issue of image de-noising, but its mechanism is very complex, so it is not suitable for those applications with high requirements of real-timing property. In order to resolve the above problem, Easley et al. proposed non-subsampled shearlet transform (NSST) [21] which combined the non-subsampled Laplacian pyramid transform with several different shearing filters. Compared with NSCT, NSST absorbs some recent developments in the theory of multidimensional wavelets, and shows a lot of advantages especially the property of low computational complexity. In addition, NSST also satisfies the requirement of the shift-invariance property, but its applications in image de-noising are still under exploring [22].

In this paper, we proposed a new technique for image de-noising based on NSST and IFE. Unlike the previous anti-impulse noise filters, the new one is not to give a weight value to each pixel in the filter window simply, but to firstly adaptively get the membership degree and non-membership degree values by certain function, then, from the view of the information quantity, to figure out the intuitionistic fuzzy entropy value which will examine the former two values, lastly to obtain the final weight value. The theory analysis and simulation results show that the new method can not only filter impulse noises effectively, but also protect the image details and edges excellently. As a result, the applied future of the technique in the fields of image target detection and missile precise guidance is very promising. In order to overcome this disadvantage, we address an algorithm in the NSST domain for image de-noising.

The remainder of this paper is organized as follows. A brief review of NSST theory is introduced in Section 2. In Section 3, the improved IFE model and its mathematical morphology are presented in detail. Section 4 describes the proposed algorithm based on NSST and improved IFE, as well as its concrete steps. Section 5 reports the experimental results of our technique and the comparisons with other typical methods. The conclusion and the next effort are drawn in the end.

2. Non-subsampled shearlet transform

The details of the basic NSST [21] model are introduced as follows.

Let dimension $n = 2$, the affine systems of shearlet transform (ST) can be expressed as follows.

$$\{\psi_{j,l,k}(x) = |\det A|^{j/2}\psi(S^l A^j x - k) : l, \quad j \in Z,\ k \in Z^2\} \tag{1}$$

where ψ is a collection of basis function and satisfies $\psi \in L^2(R^2)$; A denotes the anisotropy matrix for multi-scale partitions, S is a shear matrix for directional analysis. j, l, k are scale, direction and shift parameter respectively. A, S are both 2×2 invertible matrices and $|\det S| = 1$. For each $a > 0$ and $s\in\mathbf{R}$, the matrices of A and S are given as follows.

$$A = \begin{pmatrix} a & 0 \\ 0 & \sqrt{a} \end{pmatrix}, \quad S = \begin{pmatrix} 1 & s \\ 0 & 1 \end{pmatrix} \tag{2}$$

Assume $a = 4$, $s = 1$, Eq. (2) can be modified further.

$$A = \begin{pmatrix} 4 & 0 \\ 0 & 2 \end{pmatrix}, \quad S = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix} \tag{3}$$

For any $\xi = (\xi_1, \xi_2) \in \hat{R}^2$, $\xi_1 \neq 0$, the mathematical expression of basic function $\hat{\psi}^{(0)}$ for ST can be given by [21]

$$\hat{\psi}^{(0)}(\xi) = \hat{\psi}^{(0)}(\xi_1, \xi_2) = \hat{\psi}_1(\xi_1)\hat{\psi}_2\left(\frac{\xi_2}{\xi_1}\right) \tag{4}$$

where $\hat{\psi}$ is the Fourier transform of ψ. $\hat{\psi}_1 \in C^\infty(R)$, $\hat{\psi}_2 \in C^\infty(R)$ are both wavelet, and $\sup p\hat{\psi}_1 \subset [-1/2,\ -1/16] \cup [1/16,\ 1/2]$, $[-1, 1]$. It implies that $\hat{\psi}_0 \in C^\infty(R)$ and compactly supported with $\sup p\hat{\psi}_0 \subset [-1/2,\ 1/2]^2$. In addition, we assume that

$$\sum_{j\geq 0} |\hat{\psi}_1(2^{-2j}\omega)|^2 = 1, \quad |\omega| \geq \frac{1}{8} \tag{5}$$

And for each $j \geq 0$, $\hat{\psi}_2$ satisfies that

$$\sum_{l=-2^j}^{2^j-1} |\hat{\psi}_2(2^j\omega - l)| = 1, \quad |\omega| \leq 1 \tag{6}$$

From the conditions on the support of $\hat{\psi}_1$, $\hat{\psi}_2$ one can obtain that the function $\psi_{j,l,k}$ has the frequency support listed below:

$$\sup p\hat{\psi}^0_{j,l,k} \subset \left\{(\xi_1, \xi_2)|\xi_1 \in [-2^{2j-1}, -2^{2j-4}] \cup [2^{2j-4}, 2^{2j-1}], \left|\frac{\xi_2}{\xi_1} + l2^{-j}\right| \leq 2^{-j}\right\} \tag{7}$$

That is, each element $\hat{\psi}_{j,l,k}$ is supported on a pair of trapeziform zones, whose sizes all approximate to $2^{2j} \times 2^j$. The tiling of the frequency by shearlet and the size of the frequency support of $\psi_{j,l,k}$ are illustrated in Fig. 1. Note that Fig. 1(b) only shows the frequency support for $\xi_1 > 0$; the figure of the other support for $\xi_1 < 0$ is symmetrical.

NSST combines the non-subsampled Laplacian pyramid (NSLP) transform with several different combinations of the shearing filters (SF). It is commonly acknowledged that NSST is the shift-invariant version of ST essentially. In order to eliminate the courses of up-sampling and sub-sampling, NSST utilizes NSLP filters as a substitute for the Laplacian pyramid filters used in the ST mechanism, so that it has superior performance in terms of shift-invariance, multi-scale and multi-directional properties. The discretization process of NSST is composed of two phases including multi-scale factorization and multi-directional factorization. NSLP is utilized to complete multi-scale factorization. The first phase ensures the multi-scale property by using two-channel non-subsampled filter bank, and one low frequency image and one high frequency image can be produced at each NSLP decomposition level. The subsequent NSLP decompositions are implemented to decompose the low frequency component available iteratively to capture the singularities in the image. The multi-directional factorization in NSST is realized via improved SF. These filters are formed by avoiding the sub-sampling to satisfy the property of shift-invariance. SF allows the direction decomposition with l stages in high frequency images from NSLP at each level and produces 2^l directional sub-images with the same size as the source image. Fig. 2 illustrates the two-level NSST decomposition of an image. The number of shearing directions is chosen to be 4 and 4 from finer to coarser scale.