ELectronics EXpress

LETTER

IEICE Electronics Express, Vol.11, No.17, 1–11

A novel optimization design approach for Contourlet directional filter banks

Songjun Zhang[1]**, Guoan Yang**[2a)]**, Zhengxing Cheng**[1]**,**
Huub van de Wetering[3]**, Chihiro Ikuta**[4]**, and Yoshifumi Nishio**[4]

[1] *School of Mathematics and Statistics, Xi'an Jiaotong University, Xi'an 710049, China*

[2] *School of Electronics and Informations, Xi'an Jiaotong University, Xi'an 710049, China*

[3] *Department of Mathematics and Computer Science, Eindhoven University of Technology, The Netherlands*

[4] *Department of Electrical and Electronic Engineering, Tokushima University, 770–8506 Japan*

a) *gayang@mail.xjtu.edu.cn*

Abstract: A Contourlet transform, an expansion of a wavelet transform, is a double filter bank structure composed of Laplacian Pyramid and directional filter banks. Several wavelet filters of preferable performance have been developed for wavelet transforms, e.g. CDF (Cohen, Daubechies and Feauveau) 9/7 filter. However, there is still only a limited number of wavelet filters applicable for Contourlet transforms. Therefore, it has become an urgent issue to find effective contourlet filters and design methods in the field of multiscale geometric analysis. In order to design a new directional filter bank for Contourlet transforms, this paper uses parametric modeling to obtain a novel PKVA (See-May Phoong, Chai W. Kim, P. P. Vaidyanathan, and Rashid Ansari) filter, by first implementing Chebyshev best uniform approximation, and then reaching the optimal solution by means of Parks-McClellan algorithm. Using Brodatz standard texture image database for test images, and using image denoising treated with hidden Markov tree (HMT) models in the Contourlet domain, the optimal PKVA filter was obtained on the basis of the peak signal to noise ratio (PSNR) maximum criterion with human visual properties considered. Experiment results show that the image denoising performance of our filter is better than that of Po and Do's. The PSNR obtained from the experiment is 1.011449 higher than that of Po and Do's in average. Therefore, Contourlet transforms using the proposed PKVA filter as DFB can ensure that the local error in images is of a uniform minimum value, and that good overall visual effect can be achieved.

Keywords: Contourlet, PKVA filter, directional filter banks, Chebyshev best uniform approximation, image denoising

Classification: Electron devices, circuits, and systems

DOI: 10.1587/elex.11.20140556
Received June 10, 2014
Accepted July 22, 2014
Publicized August 13, 2014
Copyedited September 10, 2014

ELectronics EXpress
IEICE Electronics Express, Vol.11, No.17, 1–11

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1 Introduction

Contourlet transforms, proposed by M. N. Do and M. Vetterli in 2002, form a new tool for multiscale geometric analysis, which can represent natural images more sparsely, and has less redundancy and better approximation performance compared with Ridgelets, Curvelets, and other multiscale geometric analysis tools [1]. Since the support set of a Contourlet transform is a rectangle, the end result is to approximate contours with lines [2]. Contourlet transforms have anisotropic scaling relations similar to Curvelets, which can effectively represent the contours and edge information of images. Therefore, a Contourlet transform is a “true” two-dimensional representation of images. However, the regularity of the basis function of Contourlet transforms is still not high enough, and time-frequency-localized image representation is also not ideal. Furthermore, frequency aliasing and defects in both the mathematical model and the theory of Contourlet transform exist. At present, research of Contourlet transforms is focusing on, among others, anti-aliasing, Contourlet transforms based on wavelets, and non-subsampled Contourlet transforms. Applications of Contourlet transforms mainly include image denoising, image coding, image recognition, and image retrieval. So far, some progress has been made in image denoising and image retrieval in Contourlet transforms based on hidden Markov models [3].

A contourlet transform, also named pyramidal directional filter bank, is a double filter bank structure composed of a Laplacian Pyramid (LP) and Directional Filter Banks (DFB). Currently, there are few filters for Contourlet transforms, and they are basically borrowed from wavelet filters which have better performance (e.g., 9/7 filter, Haar filter, PKVA filter, etc.). Although primary research results have been achieved concerning Contourlet transforms using 9/7 filter and PKVA

DOI: 10.1587/elex.11.20140556
Received June 10, 2014
Accepted July 22, 2014
Publicized August 13, 2014
Copyedited September 10, 2014

DOI: 10.1587/elex.11.20140556
Received June 10, 2014
Accepted July 22, 2014
Publicized August 13, 2014
Copyedited September 10, 2014

filters, significant differences exist between the wavelet bases and the Contourlet bases, and large defects appear when applying wavelet bases directly [4, 5]. Therefore, improving the design of filters for Contourlet transforms remains a core issue in multiscale geometric analysis.

Consequently, although Contourlet transforms form an effective approach for representation of singular lines, especially in contour and feature extraction, research on the design and optimization of Contourlet filters is still needed. Therefore, DFB design for Contourlet transforms is a challenging area of multiscale geometric analysis, and any progress in this area will contribute to the further deepening and improvement of multiscale geometric analysis, especially Contourlet transform theory [7, 8]. Contourlet transforms can be applied in image processing, computer vision, and pattern recognition, for improving the efficiency of edge detection, the correct recognition rate in image retrieval, and so on. The study presented is an exploration of a design and optimization approach for DFB aimed to find optimal PKVA filters for Brodatz standard texture image database for image denoising in Contourlet HMT models.

This paper is organized as follows: Section 2 proposes a PKVA filter design approach based on the theory of Chebyshev best uniform approximation. In section 3, we demonstrate the image denoising application of the proposed PKVA using HMT models. An optimal DFB is recommended, and experiment results are presented and discussed. Section 4 concludes the paper with a summary of the most important findings and an evaluation of the study in comparison with other research.

2 PKVA design for DFB

Proposition 1 The DFB provides a biorthogonal or orthogonal expansion if and only if its kernel QFB's are biorthogonal or orthogonal, respectively.

Therefore, the design issue for the DFB essentially amounts to the design of QFB's with the desired properties. For synthesis of biorthogonal quincunx systems, there are two main approaches. One uses the McClellan transformation to map 1-D biorthogonal two channel filter banks to 2-D biorthogonal solutions [9]. The other is based on polyphase mapping and leads to efficient filter banks that use the ladder structure where all the operations are separable. The filter obtained by the second approach is a PKVA filter.

2.1 PKVA filter

Let $\{h, g, \widetilde{h}, \widetilde{g}\}$ be a biorthogonal FIR wavelet filter bank with an analysis highpass filter g, an analysis lowpass filter h, and with their polyphase representations given by

$$h(z) = h_e(z^2) + z^{-1}h_o(z^2),$$
$$g(z) = g_e(z^2) + z^{-1}g_o(z^2),$$

where $h_e(z) = \sum_k h_{2k}z^{-k}$, $h_o(z) = \sum_k h_{2k+1}z^{-k}$, $g_e(z) = \sum_k g_{2k}z^{-k}$, and $g_o(z) = \sum_k g_{2k+1}z^{-k}$. Thus, the polyphase matrices of the filter bank are

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$$P(z) = \begin{bmatrix} h_e(z) & h_o(z) \\ g_e(z) & g_o(z) \end{bmatrix}$$

and

$$\tilde{P}(z) = \begin{bmatrix} \tilde{h}_e(z) & \tilde{h}_o(z) \\ \tilde{g}_e(z) & \tilde{g}_o(z) \end{bmatrix}.$$

Let

$$P(z) = \begin{bmatrix} z^{-N_1} & \beta(z) \\ 0 & z^{-N_2} \end{bmatrix},$$

then the analysis filter pair is:

$$h(z) = z^{-2N_1} + z^{-1}\beta(z^2), \quad g(z) = z^{-(2N_2+1)}.$$

So, $h(z)$ can be designed to be a good lowpass filter, but $g(z)$ is all-pass, which is not useful for subband coding applications. We can modify $g(z)$ without affecting $h(z)$ by taking the polyphase matrix to be:

$$P(z) = \begin{bmatrix} 1/2 & 0 \\ -\frac{1}{2}\alpha(z) & 1 \end{bmatrix} \begin{bmatrix} z^{-N_1} & \beta(z) \\ 0 & z^{-N_2} \end{bmatrix}$$
$$= \begin{bmatrix} \frac{1}{2}z^{-N_1} & \frac{1}{2}\beta(z) \\ -\frac{1}{2}z^{-N_1}\alpha(z) & -\frac{1}{2}\alpha(z)\beta(z) + z^{-N_2} \end{bmatrix}.$$

In fact, for $\alpha(z) = \beta(z)$ and $N_2 = 2N_1 - 1$, $g(z)$ is an ideal highpass filter. In this case, we have the polyphase matrices:

$$P(z) = \begin{bmatrix} \frac{1}{2}z^{-N} & \frac{1}{2}\beta(z) \\ -\frac{1}{2}z^{-N}\beta(z) & -\frac{1}{2}\beta^2(z) + z^{-2N+1} \end{bmatrix}$$
$$\tilde{P}(z) = \begin{bmatrix} -\frac{1}{2}\beta^2(z) + z^{-2N+1} & -\frac{1}{2}\beta(z) \\ \frac{1}{2}z^{-N}\beta(z) & \frac{1}{2}z^{-N} \end{bmatrix}.$$

With this, we get the following expressions for the analysis and the synthesis filter pair, respectively:

$$\begin{cases} h(z) = (z^{-2N} + z^{-1}\beta(z^2))/2 \\ g(z) = -\beta(z^2)h(z) + z^{-4N+1} \\ \tilde{h}(z) = -g(-z) \\ \tilde{g}(z) = h(-z) \end{cases} \tag{1}$$

If $\beta(z)$ has the following magnitude and phase response:

$$|\beta(e^{j2\omega})| = 1, \ \forall\, \omega$$
$$\angle\beta(e^{j2\omega}) = \begin{cases} (-2N+1)\omega & , \text{ for } \omega \in [0, \pi/2] \\ (-2N+1)\omega \pm \pi & , \text{ for } \omega \in [\pi/2, \pi] \end{cases}, \tag{2}$$

$\{h, g\}$ is an ideal lowpass and highpass filter pair.

DOI: 10.1587/elex.11.20140556
Received June 10, 2014
Accepted July 22, 2014
Publicized August 13, 2014
Copyedited September 10, 2014

The ideal choice of $\beta(z)$ as in (2) requires infinite complexity. Therefore, we have to design $\beta(z)$ to approximate the conditions in (2). However, the approximation will not change the perfect reconstruction property because the analysis polyphase matrix $P(z)$ and the synthesis polyphase matrix $\widetilde{P}(z)$ satisfy $P(z)\widetilde{P}(z) = \frac{1}{2}z^{-3N+1}I$, regardless of the choice of $\beta(z)$.

Let

$$\beta(z) = \sum_{k=1}^{N} v_k(z^{-N+k} + z^{-N-k+1}), \tag{3}$$

where the coefficients v_k satisfy $\sum_{k=1}^{N} v_k = \frac{1}{2}$. Thus, we get a linear phase FIR biorthogonal filter bank.

We know that the higher regularity of wavelets, the less number of the wavelet coefficients in the wavelet domain, while the regularity of a wavelet is changed with vanishing moments of wavelet. For biorthogonal wavelets, the vanishing moments of wavelet function Ψ and $\widetilde{\Psi}$ depend on the number of zeros of $h(\omega)$ and $\widetilde{h}(\omega)$ at $\omega = \pi$; that is, the number of zeros of $h(z)$ and $\widetilde{h}(z)$ when $z = -1$, respectively. From (1), we can see that $h(z)$ and $\widetilde{h}(z)$ have the same number of zeros at the same condition. Note that

$$h(z) = (z^{-2N} + z^{-1}\beta(z^2))/2 = z^{-2N}\left(1 + \textstyle\sum_{k=1}^{N} v_k(z^{2k-1} + z^{-2k+1})\right)/2,$$

Let $F_h(z) = 1 + \sum_{k=1}^{N} v_k(z^{2k-1} + z^{-2k+1})$, then the number of zeros of $h(z)$ at $z = -1$ is equivalent to the number of zeros of $F_h(z)$ at $z = -1$. Assuming $h(z)$ has zeros of order p at $z = -1$, we have the following:

$$F_h^{(i)}(z)|_{z=-1} = 0, \quad 1 \le i \le p-1.$$

Note that, if i is odd, the above equation always holds, and if i is even, we have the following equation:

$$\sum_{k=1}^{N} v_k(2k-1)^{2l} = 0, \quad 1 \le l \le r-1, \tag{4}$$

where $p = 2r - 1$.

Theorem 2 If the vanishing moments of biorthogonal wavelets Ψ and $\widetilde{\Psi}$ are p and $\widetilde{p}$, respectively, then the length of their support is at least $p + \widetilde{p} - 1$.

Therefore, the maximum number of zeros of $h(z)$ is $2N - 1$, and when $p = 2N - 1$, that is $r = N$, we get the following equation:

$$\begin{pmatrix} x_1^0 & x_2^0 & \cdots & x_N^0 \\ x_1^2 & x_2^2 & \cdots & x_N^2 \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{2(N-1)} & x_2^{2(N-1)} & \cdots & x_N^{2(N-1)} \end{pmatrix} \begin{pmatrix} v_1 \\ v_2 \\ \vdots \\ v_N \end{pmatrix} = \begin{pmatrix} 1/2 \\ 0 \\ \vdots \\ 0 \end{pmatrix} \tag{5}$$

where $x_k = 2k - 1$, $k = 1, 2, \ldots, N$. As the matrix is nonsingular, the solution for $\{v_k : k = 1, 2, \ldots, N\}$ will always exist. Thus, we can get a pair of maximally flat FIR biorthogonal wavelet filters.

Next, we will map the 1-D biorthogonal filter banks into the 2-D quincunx filter banks with perfect reconstruction. Let $\beta(z) = \beta(z_0)\beta(z_1)$ with $z^{-1} = z_0^{-1}z_1^{-1}$, then the

DOI: 10.1587/elex.11.20140556
Received June 10, 2014
Accepted July 22, 2014
Publicized August 13, 2014
Copyedited September 10, 2014

IEICE Electronics Express, Vol.11, No.17, 1–11

polyphase matrix of the 2-D quincunx filter banks can be written as:

$$P(z_0,z_1)=\begin{bmatrix}\frac{1}{2}(z_0z_1)^{-N} & \frac{1}{2}\beta(z_0)\beta(z_1)\\ -\frac{1}{2}(z_0z_1)^{-N}\beta(z_0)\beta(z_1) & -\frac{1}{2}\beta^2(z_0)\beta^2(z_1)+(z_0z_1)^{-2N+1}\end{bmatrix},$$

$$\widetilde{P}(z_0,z_1)=\begin{bmatrix}-\frac{1}{2}\beta^2(z_0)\beta^2(z_1)+(z_0z_1)^{-2N+1} & -\frac{1}{2}\beta(z_0)\beta(z_1)\\ \frac{1}{2}(z_0z_1)^{-N}\beta(z_0)\beta(z_1) & \frac{1}{2}(z_0z_1)^{-N}\end{bmatrix}.$$

And the analysis and synthesis polyphase matrices satisfy $P(z)\widetilde{P}(z)=\frac{1}{2}(z_0z_1)^{-3N+1}I$, so the perfect reconstruction property is preserved. From these polyphase matrices, we can get the analysis and synthesis quincunx filter banks as follows.

$$\begin{cases} h(z_0,z_1)=(z_0^{-2N}+z_0^{-1}\beta(z_0z_1^{-1})\beta(z_0z_1))/2\\ g(z_0,z_1)=-\beta(z_0z_1^{-1})\beta(z_0z_1)h(z_0,z_1)+z_0^{-4N+1}\\ \widetilde{h}(z_0,z_1)=-g(-z_0,-z_1)\\ \widetilde{g}(z_0,z_1)=h(-z_0,-z_1)\end{cases} \tag{6}$$

If the 1-D transfer function $\beta(z)$ approximates the conditions in (2) well, $h(z_0,z_1)$ and $g(z_0,z_1)$ are diamond and diamond-complement filters, respectively.

2.2 Chebyshev best uniform approximation

For a continuous function $f(x)$ on the interval $[a,b]$, there will be only one polynomial $\hat{p}(x)$ in the set P_n of all n polynomials, which satisfies the following equation:

$$\max_{a\le x\le b}|\hat{p}(x)-f(x)|=\min\{\max_{a\le x\le b}|p(x)-f(x)|\},$$

where $p(x)\in P_n$.

For the linear phase FIR filter $h(z)=\sum_{k=0}^{N-1}h_ke^{-jk\omega}$, we may assume that $h(z)$ is positive symmetric, and N is odd, then:

$$h(z)=z^{-(N-1)/2}h_g(z),\quad z=e^{j\omega},$$

where $h_g(z)=h_g(e^{j\omega})=\sum_{n=0}^{M}a(n)\cos(n\omega)$, $M=(N-1)/2$, and $a(n)$ is defined as follows:

$$a(n)=\begin{cases}h_{(N-1)/2} & ,\ n=0\\ 2h_{(N-1)/2-n} & ,\ n=1,2,\ldots,(N-1)/2\end{cases}.$$

Assume $h_{new}(e^{j\omega})$ is the desired function:

$$h_{new}(e^{j\omega})=\begin{cases}1 & ,\ 0\le\omega\le\omega_p\\ 0 & ,\ \omega_s\le\omega\le\pi\end{cases}, \tag{7}$$

where ω_p and ω_s are the passband and stopband frequencies, respectively. Let $B_p=[0,\omega_p]$ and $B_s=[\omega_s,\pi]$ be the frequencies of the passband and the stopband, respectively. Let $F=B_p\bigcup B_s$, then by definition we know that $F\subseteq[0,\pi]$.

We define the weight function as follows:

$$W(e^{j\omega})=\begin{cases}1/k & ,\ 0\le\omega\le\omega_p,\ k=\delta_1/\delta_2\\ 1 & ,\ \omega_s\le\omega\le\pi\end{cases}.$$

DOI: 10.1587/elex.11.20140556
Received June 10, 2014
Accepted July 22, 2014
Publicized August 13, 2014
Copyedited September 10, 2014

Consequently, the error function is as follows:

$$E(e^{j\omega}) = W(e^{j\omega})[h_g(e^{j\omega}) - h_{new}(e^{j\omega})] = W(e^{j\omega})\left[\sum_{n=0}^{M} a(n)\cos(n\omega) - h_{new}(e^{j\omega})\right].$$

Theorem 3 (Alternation Theorem) If $p(\omega)$ is a linear combination of M cosine functions (i.e. $p(\omega) = \sum_{n=0}^{M-1} a(n)\cos(n\omega)$), then a necessary and sufficient condition for $p(\omega)$ to be the unique best-weighted Chebyshev approximation to a continuous function $h_{new}(e^{j\omega})$ on F is that the weighted error function $E(e^{j\omega})$ exhibits at least $M+2$ extremal frequencies in F. That is, points $\{\omega_i\}$ such that $\omega_0 < \omega_1 < \omega_2 < \cdots < \omega_{M+1}$, $E(e^{j\omega_i}) = -E(e^{j\omega_{i+1}})$, $i = 0, 1, 2, \cdots, M$, and $|E(e^{j\omega_i})| = \max_{\omega \in F} |E(e^{j\omega})|$.

According to the above theorem, we have:

$$W(e^{j\omega_k})\left[h_{new}(e^{j\omega_k}) - \sum_{n=0}^{M} a(n)\cos(n\omega_k)\right] = (-1)^k \rho, \tag{8}$$

where $k = 0, 1, \cdots, M+1$, and $\rho = \max_{\omega \in F} |E(e^{j\omega})|$.

With equation (8), we can get only one solution of $a(n)$, $n = 0, 1, \cdots M$ and ρ, so that we get the desired filter. However, since directly solving the equation (8) is difficult, we can solve the above equation by Remez algorithm, that is, the Parks-McClellan algorithm to obtain the desired filter.

3 Results and analysis

The PKVA filter family designed in this study was applied in image denoising through hidden Markov tree models in the Contourlet domain, with Brodatz standard texture image database as the test objects. By analyzing the experiment results, we obtained two optimal PKVA filters for texture image based on the peak signal to noise ratio (PSNR) as shown in Table I.

Table I. The coefficient v_k in equation (3) for optimal PKVA filters.

Control Parameter	Coefficient v_k in equation (3)					
0.48	0.635940	−0.212241	0.125984	−0.090210	0.069231	−0.206109
0.47	0.635291	−0.209614	0.122377	−0.085136	0.062993	−0.136772

In the experiment, we added random Gaussian noise for all images in Brodatz standard texture image database with the adding noise parameters α ($\alpha^2/255^2$) is the variance of the Gaussian noise normalized to the image range) being either 10, 20, 30, 40, or 50. And image denoising was implemented. It is found from the results that for all adding noise parameters, the number of images with maximum PSNR was larger than that of others when the control parameter γ ($\omega_p = \gamma\pi$ is the passband edge in equation (7)) of the PKVA filter is either 0.48 or 0.47. The results are shown in Fig. 1, 2, and 3. The experiment also shows that the PSNR clearly reduced when the control parameter was outside $[0.3, 0.5]$.

Objective comparison of experimental statistics of maximum PSNR with different adding noise parameters for test images in the Brodatz standard texture image database are shown in Table II.

DOI: 10.1587/elex.11.20140556
Received June 10, 2014
Accepted July 22, 2014
Publicized August 13, 2014
Copyedited September 10, 2014

IEICE Electronics Express, Vol.11, No.17, 1–11

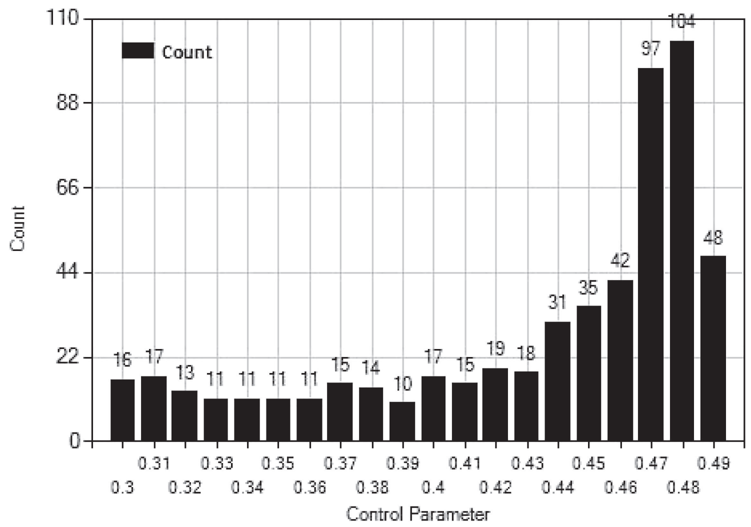

Fig. 1. The number of times PSNR is maximum with different control parameters.

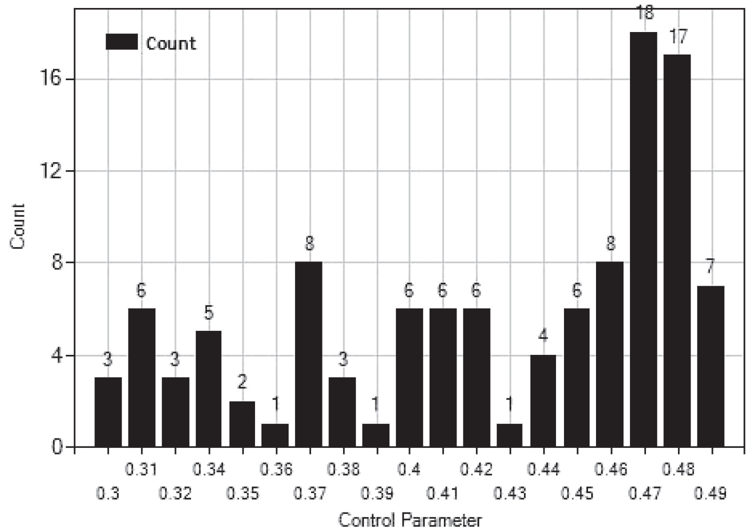

Fig. 2. The number of times PSNR is maximum with different control parameters when adding noise parameter is 10.

Table II. Comparison between experiment results of PKVA filter designed in this paper and performances of Po and Do's PKVA filter.

Adding Noise Parameter	Total amount of images	Po and Do	0.47	Mean differences	0.48	Mean differences
10	111	24.976405	26.270900	+1.294495	26.575702	+1.599297
20	111	25.114868	26.209089	+1.094221	26.442935	+1.328067
30	111	25.912179	26.705407	+0.793228	26.907501	+0.995322
40	111	26.801758	27.517241	+0.715483	27.555005	+0.753247
50	111	27.570614	27.944214	+0.373600	27.928166	+0.357552
All	555	26.081925	26.943073	+0.861148	27.093374	+1.011449

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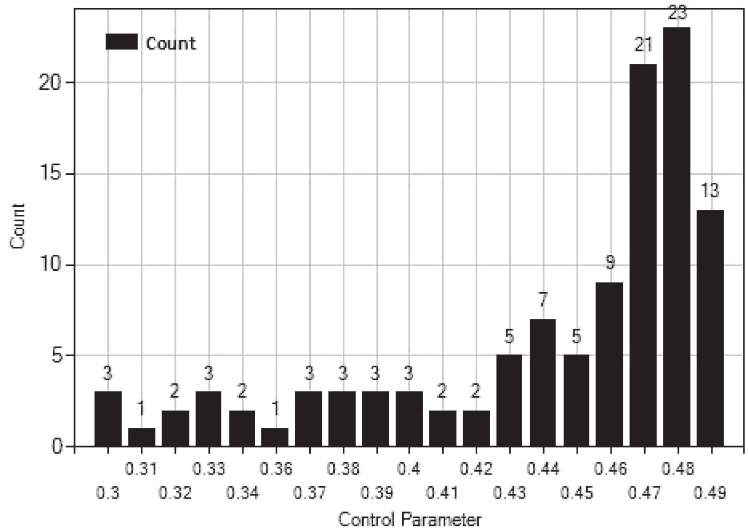

Fig. 3. The number of times PSNR is maximum with different control parameters when adding noise parameter is 40.

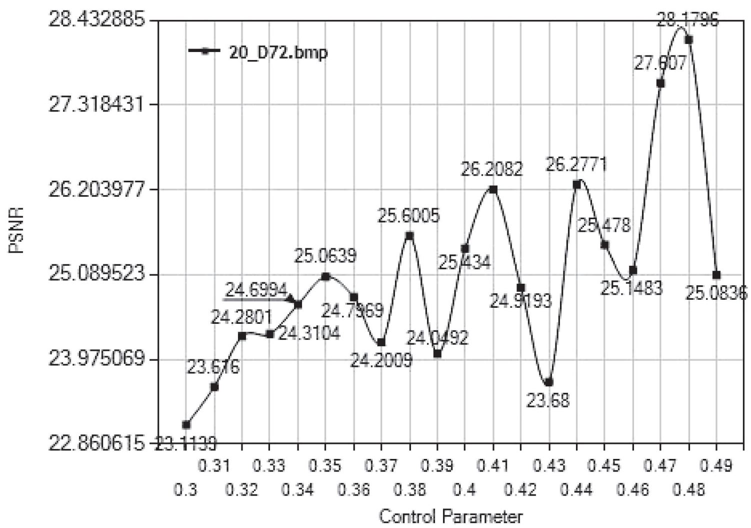

Fig. 4. The PSNR value of the test image D72 with different control parameters when adding noise parameter is 20.

Subjective comparison of denoising performances between our new PKVA filter and Po and Do's filter for test images D62 and D72 in the Brodatz standard texture image database with adding noise parameter 20 and 20 respectively, are shown in Fig. 5, 6, 7, 8, and 9.

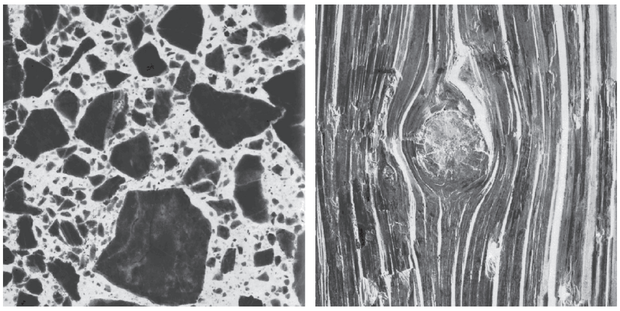

Fig. 5. Original two images from left to right: D62, D72

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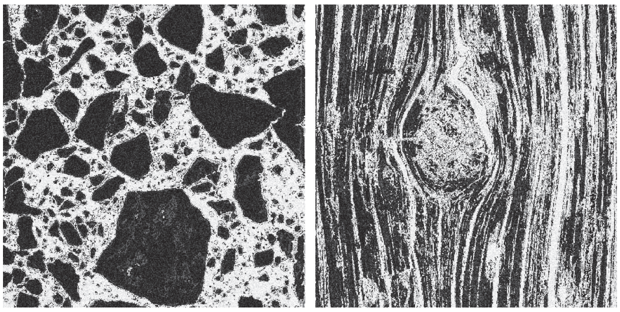

Fig. 6. The two images from left to right: D62 and D72 with adding noise parameter 20 respectively.

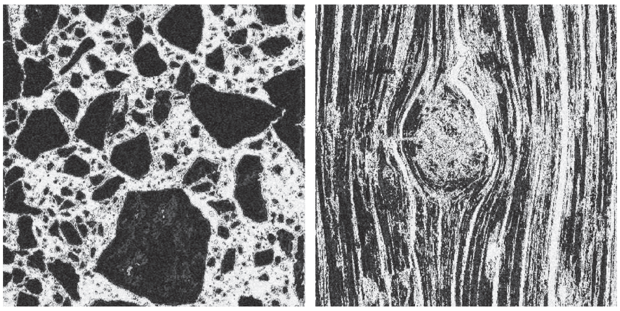

Fig. 7. Denoised images with Po and Do's filter from left to right: D62, D72

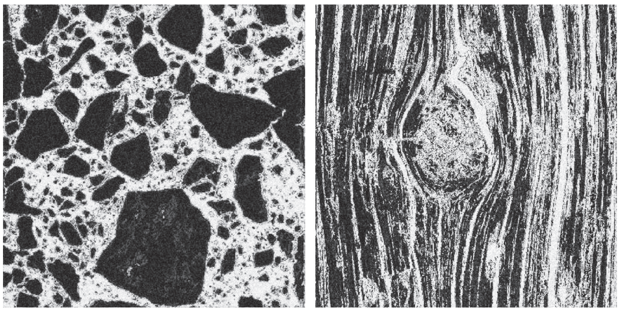

Fig. 8. Denoised images with the new PKVA filter when control parameter is 0.47 from left to right: D62, D72

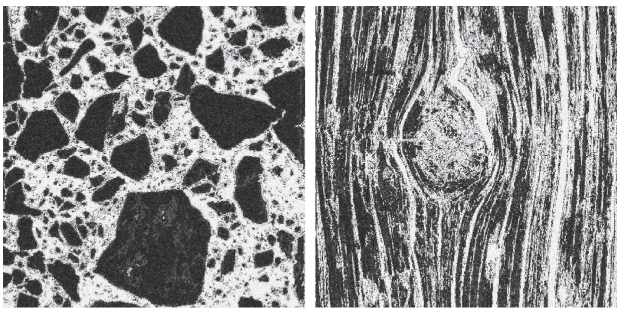

Fig. 9. Denoised images with the new PKVA filter when control parameter is 0.48 from left to right: D62, D72

DOI: 10.1587/elex.11.20140556
Received June 10, 2014
Accepted July 22, 2014
Publicized August 13, 2014
Copyedited September 10, 2014

IEICE Electronics Express, Vol.11, No.17, 1–11

4 Conclusions

This paper proposed a new PKVA filter design approach for the contourlet transform based on Chebyshev best uniform approximation method. It proved to be effective, and PKVA 12 filter for Brodatz standard texture image denoising in the contourlet HMT models was improved by 1.599297 dB. Meanwhile, the subjective comparison was as good as the experimental results of Po and Do in the reference [3].

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