A performance comparison of two PWS filters in different domain for image reconstruction technique under different image types

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ABSTRACT

Due to many factors that can be degraded an image quality from the desired version. Image reconstruction application is the method that aims to recover those degradations based on mathematical and statistical models. Partition-based weighted sum (PWS) filtering is one of the most effective techniques for application of an image restoration and reconstruction. In this paper, we compare two PWS filters in both frequency and spatial domain under several image types. Two PWS filters include hard partition-based weighted sum (HPWS) filter and subspace hard partition-based weighted sum (S-HPWS) filter. Five image types are considered including aerial images, human images, miscellaneous images, object images and text images. The simulation results show that the spatial domain HPWS filter offers the best performance when we apply to restore object image, but this filter not successful in term of memory usage and complexity of computation. Frequency domain S-HPWS filter, which required less memory and computation time using PCA technique to reduce size of data, offers good performance when we attempt to restore miscellaneous image. On the other hand, text image gets poor performance from all types of filters.

Keywords: WS filter, HPWS, LMS, Wiener filter, S-HPWS, VQ, PCA

1. INTRODUCTION

During the past decade, image restoration and reconstruction have become more important in the field of image processing because there are increased utilized imagery in many application couple with improvement in quality of the image, speed and complexity of the algorithm. Purpose of the image restoration and reconstruction is to reconstruct the desired image from image recorded in the presence of one or more sources of degradation. The degradation can be during acquisition the image because of the imperfection of the process and/or during transmission process. Degradation forms consist of natural loss of spatial resolution caused by optical distortion, motion blur due to limited shutter speed, aliasing effect caused by imperfection of sampling process, noise that occurs within the sensor or during transmission [1]. For the most widely used techniques in an image restoration and reconstruction application is filtering.

Non-linear filters are often utilized to treat impulsive noise. In contrast, non-linear filters, such as the median filters [2] which neighbouring pixels are ranked according to intensity and the median value becomes the new value for centre pixel and the rank conditioned rank selection (RCRS) filters [3] which use the rank of selected input samples as the basis for the output rank selection, preserve edge, in case of image corrupted by Gaussian noise, these filters have no improvement over linear filter. On the other hand, linear filters, such as weighted sum (WS) linear filters are normally utilized to treat widely encountered additive white Gaussian noise (AWGN). Nonetheless, the non-stationary nature of natural images yields poor performance. For instance, the application of Wiener filters for image denoising typically utilizes a single linear kernel to estimate a non-stationary process. The Wiener filter can implement in both frequency domain and spatial domain. These are commonly derived in the sense to minimize the mean square error (MSE) between the desired image and the degraded image. However, Wiener filters successfully smooth flat region, but fail to handle edges. Spatially adaptive filter, such as partition-based weighted

Spatially adaptive filter, such as partition-based weighted sum (PWS) filter proposed by Barner *et al.* [4] which combines linear filtering theory with data adaptive observation space partitioning, approach to dealing with a non-stationary signal. The PWS filter is an effective algorithm for processing non-stationary signals, especially those with regularly oc-

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curring structure, such as images. PWS filter was originally introduced for utilizing hard partitioning, which partition the observation space into mutually exclusive region [4-7] using vector quantization (VQ) [7-9], known as hard partition-based weighted sum (HPWS) filter. In addition, the general framework of the HPWS filter is to partition the observation space through hard threshold of VQ. The unique filtering operation is defined by each partition the observation space. This operation can include any type of linear or non-linear filter. Alternatively, the least mean square (LMS) algorithm can be applied to each partition independently if suitable training data is available. VQ is an effective technique of data classification and compression based on block coding. VQ identify an input vector with member in codebook based on error measure criteria. However, VQ has some difficulties such as efficiency of codebook design. The most famous technique that used to generate the codebook is Linde-Buzo-Gray (LBG) algorithm [8-9]. LBG algorithm is an iterative technique to modify the codebook for better than the starting initial codebook.

Later, Lin *et al.* was improved the HPWS filter by used dimension reduction application of principal component analysis (PCA) to reduced large size of HPWS window known as subspace hard partition-based weighted sum (S-HPWS) filter [10-11]. PCA also known as Karhunen-Love (KL) transform that is become one of the most successful approach in pattern recognition, such as face and vehicle license plate. The framework of S-HPWS filter is to separate the observed image using VQ with subsequent filtration of the partitioned image and then apply to appropriate weight coefficient of filter. Due to this smaller size of window, the S-HPWS filter implemented with less burden of computation and requires less memory. By the subspace projection technique, which is dimension reduction technique of PCA, the S-HPWS filter improves the HPWS filter performance in some cases.

In this paper, we focus on the performance between the HPWS filter and S-HPWS filter in both frequency and spatial domain under different image types that degraded by Gaussian blur together with additive white Gaussian noise. Our experiments show different performance of five image types: aerial images, human images, miscellaneous images, object images and text images. The remainder of this paper is organized as follows. Section II gives the theoretical basis of vector quantization, least mean square algorithm, Wiener filter and principal component analysis. The concepts of both types of PWS filter are presented in Section III. The simulation results and performance comparisons are shown in Section IV. Finally, conclusions are presented in Section V.

2. RELATED KNOWLEDGE

The details of related knowledge to both of PWS filters will describe in this section that consist of vector quantization, least mean square algorithm and principal component analysis.

2.1 Vector Quantization

In the image vector quantization [8-9], firstly, the training images is partition into sub-block and convert them into training vectors $(y_j(k))$ in the lexicographic process. The input image can be closely represented by applied a transfer function to a specific region of the training image and replaced by codebook that generated from set of training images themselves. The codebook should be generated from statistically representative training images.

To generate the codebook (Ω), the LBG algorithm is implemented. LBG algorithm starts with define the initial value of codeword $(z_i|z_i, i = 1, 2, \ldots, M)$, where codewords are member of codebook. The good choice for the initial codewords, required by the LBG algorithm, is the observation vectors selected from the desired signal. Secondly, grouping training vectors into the codebook using minimum distortion between codebook (Ω) and training vector $(y_j(k))$. After that the codebook will update by average members in the group. This update will iterate until the distortion is under the limit. The distortion is expressed by

$$distortion(x_j, z_i) = \frac{1}{n}\sum\nolimits_{k=1}^{n} \left[y_j(k) - z_i(k)\right]^2. \quad (1)$$

To average the distortion can be obtain from

$$D_{m+1} = \frac{1}{N}\sum\nolimits_{j=1}^{N} \min d(y_j, Z_{i,m+1}). \quad (2)$$

To find the condition in order to stop update is given by

$$\frac{D_m - D_{m+1}}{D_{m+1}} \le \varepsilon \quad (3)$$

where ε is the LBG limit, k is number of member in training vector, N is size of partition of training vector, M is size of codebook, j is number of training vector and m is the iteration number.

For more understanding of the algorithm the flowchart is shown in “Fig. 1”

2.2 Least Mean Square algorithm

The LMS algorithm [12-13] is an adaptive algorithm that uses a gradient-cased method of steepest descent. The purpose of the algorithm is to adapt the weight coefficient $(w(n))$ of the filter to match closely as possible the response of an unknown system. LMS algorithm uses the estimation of the gradient vector from the available data. LMS incorporates an iterative procedure that makes successive corrections to

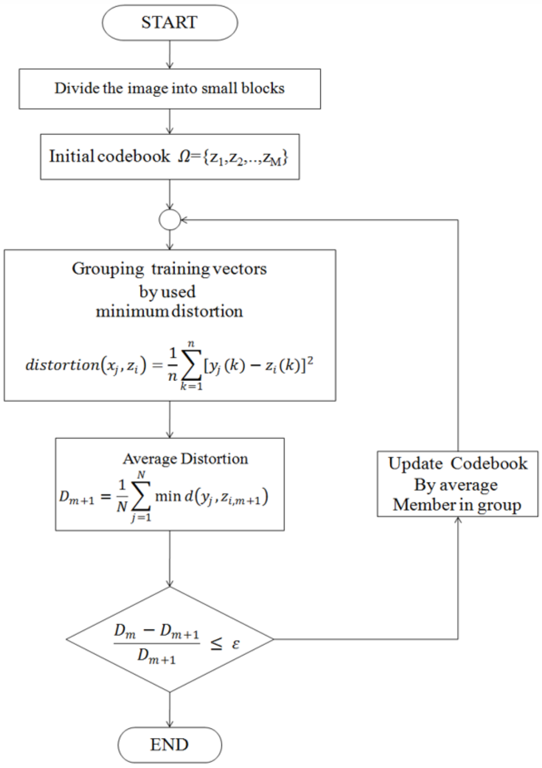

Fig.1: *Flowchart of LBG algorithm.*

weight vector in direction of the negative of the gradient vector which eventually leads to the minimum MSE. The block diagram of LMS algorithm is shown in “Fig. 2”

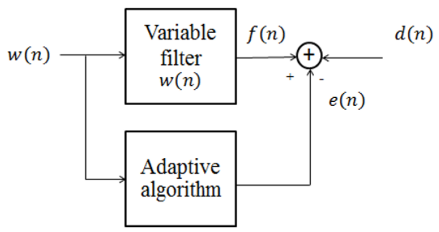

Fig.2: *Block diagram of LMS algorithm.*

From steepest descent technique, the weight coefficient vector can be expressed by

$$w(n+1) = w(n) + \frac{1}{2}\beta\left[-\nabla J(E[e^2(n)])\right]. \quad (4)$$

where J is the cost function of MSE, β is the step size which controls the rate of convergence, steady state error and stability of filter and $E[e^2(n)]$ is MSE where $e^2(n)$ is the error signal between desired signal ($d(n)$) and estimated signal ($f(n)$) that given by

$$e(n) = d(n) - f(n) \quad (5)$$

where

$$f(n) = w^T x(n). \quad (6)$$

The goal of the algorithm is to obtain the optimum weight such that the cost function is minimized. The gradient of the cost function can be given as

$$\nabla J(E[e^2(n)]) = \frac{\partial J}{\partial(w)} = -2E[e(n) \times (n)]. \quad (7)$$

By substituting Eq. (7) into Eq. (5), the weight coefficient vector of LMS algorithm can be expressed as

$$w(n+1) = w(n) + \beta e(n) \times (n). \quad (8)$$

To initiate weight coefficient vector, we can set to zero. The value of the step size (β) should be between the zero to proportion of max value of eigenvalue of autocorrelation matrix(R) of observed signal $x(n)$.

$$0 < \beta \leq \frac{1}{\lambda_{max}} \quad (9)$$

where $\lambda_m ax$ is max value of eigenvalue of (R).

2.3 Wiener Filter

There are two types of Wiener filter [14-16] that can be implemented: one is the spatial or space domain Wiener filter and the frequency domain Wiener filter.

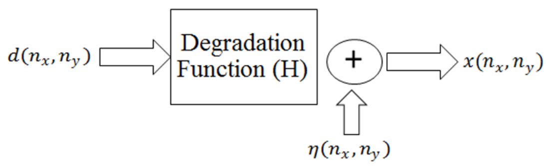

Fig.3: *Degradation model.*

The degradation model as shown in “Fig.3” consists of the degradation function together with additive noise which operates on the original image to produce the degraded image.

1) Frequency domain

In frequency domain, the performance of the filter depends on the estimation process of the desired image and noise power spectra from the observed image. The degradation process can be expressed by

$$X(n_x,n_y) = D(n_x,n_y)H(n_x,n_y) + \eta(n_x,n_y). \quad (10)$$

where $X(n_x,n_y)$ is degraded image in frequency domain, $D(n_x,n_y)$ is desired image in frequency domain, $H(n_x,n_y)$ is degradation function in frequency domain and $\eta(n_x,n_y)$ is additive noise.

The solution of the filter in frequency domain is similar to spatial domain. By minimizing the cost function (J) that given by

$$J = E\left[|D(n_x, n_y) - W(n_x, n_y)X(n_x, n_y)|^2\right] \quad (11)$$

where $W(n_x, n_y)$ is coefficient of Wiener filter in frequency domain. The first solution of the filter is given by

$$W(n_x, n_y) = \frac{E[X(n_x, n_y)D^{'}(n_x, n_y)]}{E[|X(n_x, n_y)|^2]} \quad (12)$$

$$\begin{aligned} E[X(n_x, n_y)D^*(n_x, n_y)] &= E[(D(n_x, n_y)+ \\ &\quad \eta(n_x, n_y))D^{'}(n_x, n_y)] \\ &= E[|D^{'}(n_x, n_y)|^2] \\ &= P_D \end{aligned} \quad (13)$$

$$E[|X(n_x, n_y)|^2] = P_D(n_x, n_y) + P_N(n_x, n_y) \quad (14)$$

where ' denotes complex conjugate, P_D is the power spectra of desired image and P_N is the power spectra of additive noise. Then, the coefficient of Wiener filter in frequency domain is given by

$$\begin{aligned} W(n_x, n_y) &= \frac{P_D(n_x, n_y)}{P_D(n_x, n_y) + P_N(n_x, n_y)} \\ &= \frac{H^{'}(n_x, n_y)}{|H(n_x, n_y)^2| + \frac{P_N(n_x, n_y)}{P_D(n_x, n_y)}}. \end{aligned} \quad (15)$$

The output of the filter is

$$F(n_x, n_y) = W(n_x, n_y)X(n_x, n_y) \quad (16)$$

and

$$f(n_x, n_y) = IDFT(F(n_x, n_y)) \quad (17)$$

when IDFT means the inverse discrete Fourier transform.

2) Spatial domain

In spatial domain, the degradation process can be expressed by

$$x(n_x, n_y) = d(n_x, n_y) * h(n_x, n_y) + \eta(n_x, n_y) \quad (18)$$

where $*$ is the convolution operator, $x(n_x, n_y)$ is degraded image in spatial domain, $d(n_x, n_y)$ is desired image in spatial domain, $h(n_x, n_y)$ is degradation function in spatial domain and $\eta(n_x, n_y)$ is additive noise.

The output vector of the filter is given by

$$f(n) = w^T x(n) \quad (19)$$

This form of convolution can be written as

$$f(n) = Xw \quad (20)$$

where

$$X = \begin{bmatrix} x(1) & 0 & & 0 \\ x(2) & x(1) & \cdots & 0 \\ \vdots & \ddots & & \vdots \\ x(n) & \cdots & & x(1) \end{bmatrix}$$

So the output of the filter can be expressed as

$$\begin{bmatrix} f(1) \\ f(2) \\ \vdots \\ f(n) \end{bmatrix} = \begin{bmatrix} x(1) & 0 & & 0 \\ x(2) & x(1) & \cdots & 0 \\ \vdots & \ddots & & \vdots \\ x(n) & \cdots & & x(1) \end{bmatrix} \begin{bmatrix} w(1) \\ w(2) \\ \vdots \\ w(n) \end{bmatrix}. \quad (21)$$

As the coefficients of the Wiener filter are obtained by minimizing an average square error function, as shown in Eq.16, with respect to coefficient vector.

$$\begin{aligned} \frac{\partial E[e(n)^2]}{\partial w} &= \frac{\partial}{\partial w} E\left[(d(n) - w^T x(n))^2\right] \\ &= \frac{\partial}{\partial w}(E[d^2] - 2w^T E[dx] + w^T E[xx^T]w) \\ &= 0 - 2w^T P + w^T R \end{aligned} \quad (22)$$

where $R = E[x(n)x^T(n)|x(n) \in \Omega_i]$ is the auto correlation matrix, and $P = E[d(n)x(n)|x(n) \in \Omega_i]$ is the cross correlation vector from auto correlation matrix and cross correlation vector can be expressed as

$$R = E[x(n)x^T(n)] = X^T X \quad (23)$$

$$P = E[d(n)x(n)] = X^T d. \quad (24)$$

The coefficient of Wiener filter in spatial domain is given by

$$w = R^{-1}P. \quad (25)$$

2.4 Principal Component Analysis

PCA [17-18] is a classical feature extraction and data compression method that commonly used in the field of pattern recognition, such as face recognition and vehicle license plate recognition. The purpose of PCA is to reduce data dimensionality by performing a covariance analysis between factors and eliminating the later principal components. It is a linear transformation that chooses a new coordinate system for the data set comes to lie on the axis. Mathematical concept that used in PCA covers standard deviation, covariance, eigenvectors and eigenvalues.

The PCA algorithm can be summarized as follow.

- Obtain images $U_1, U_2, \ldots, U_N$
- Represent every image U_i as vector I_i

- Compute the average of image vector (μ):

$$\mu = \frac{1}{N}\sum_{i=1}^{N} I_i \tag{26}$$

- Subtract the mean image (γ_i):

$$\gamma_i = I_i - \mu \tag{27}$$

- Compute the covariance matrix (C):

$$C = \frac{1}{N}\sum\nolimits_{i=1}^{N} \gamma_i \gamma_i^T \tag{28}$$

- Compute the eigenvectors ($V = [v_1, v_2, \ldots, v_K]$) and eigenvalues ($u$) of C. Where eigenvectors (V) known as eigenfaces or eigenspace.
- Keep only K best eigenvectors corresponding to the K largest eigenvalues.
- Each image (subtract the mean image: γ_i) in the training set can be represented as a linear combination of the K best eigenvectors:

$$\gamma_i - \mu = \sum\nolimits_{j=1}^{K} \tilde{x}_j v_i \tag{29}$$

or

$$\tilde{x}_j = v_i^T \gamma_i \tag{30}$$

- Represent γ_i as $\tilde{x} = \begin{bmatrix} \tilde{x}_1^i \\ \tilde{x}_2^i \\ \vdots \\ \tilde{x}_K^i \end{bmatrix}$

For given an unknown image (I_{test}) follows these procedure

- Normalize I: $\gamma_{test} = I_{test} - \mu$
- Project on the eigenspace:

$$\gamma_{test} - \mu = \sum\nolimits_{j=1}^{K} \tilde{x}_j v_i$$

- Represent γ_{test} as $\tilde{x}_{test} = \begin{bmatrix} \tilde{x}_{1,test} \\ \tilde{x}_{2,test} \\ \vdots \\ \tilde{x}_{K,test} \end{bmatrix}$

3. PARTITION BASED WEIGHTED SUM FILTER

In the general framework, the PWS filter uses a moving window operation (window size N). The observation vector at each position in the image is classified into one of the M partitions with a hard threshold. After an observation vector is classified, the corresponding Wiener filter is applied.

3.1 Hard Partition Based Weighted Sum Filter

In [4], let $\{d(n)\}$ and $\{x(n)\}$ be the k dimensional discrete data sequences representing vector of desired signal data and observed signal data, respectively. Note that $n = [n_1, n_2, \ldots, n_k]^T$ is a k dimensional positional index. The HPWS filter uses a moving window operation. At each location n, the N samples are spanned by an observation window. These samples form an observation vector. The observation space is defined by $x \in R^N$.
where

$$x(n) = [x_1(n), x_2(n), \ldots, x_N(n)]^T \tag{31}$$

and observation vectors can be expressed as

$$x = d + \eta \tag{32}$$

where η is the additive noise term and d is the desired image.

In HPWS filter, the observation space is divided into a set of M mutually exclusive partitions, $\Omega_1, \Omega_2, \ldots, \Omega_M$, which form Voroni regions defined by

$$\Omega_i = \{x \in R^N : \|x - z_i\|^2 \leq \|x - z_j\|^2\}, \tag{33}$$

for $j = 1, \ldots, M$ and $j \neq i$. This is a vector quantization partitioning scheme and the centroid of each partition z_i can be taken as the mean of the observation vectors in that particular partition. The output of a HPWS filter can be expressed as

$$F_{HPWS}(x(n)) = w_{p(x(n))}^T x(n) I(x \in \Omega_i) \tag{34}$$

where

$$I(event) = \begin{cases} 0 \; if \; even \; is \; false. \\ 1 \; if \; event \; is \; true. \end{cases} \tag{35}$$

The partition function $p(.) : R^N \to 1, 2, \ldots, M$ generates the partition index and is given by

$$p(x(n)) = \min \|x(n) - z_i\|^2. \tag{36}$$

The weight vectors for each corresponding partition are also generally estimated with the aid of training data. It was shown in [3] that, once the partitioning is fixed, the optimum weights, in a mean square error (MSE) sense, are found by using the Wiener weights for each partition. This is

$$w_i^* = R_i^{-1} p_i \tag{37}$$

where $i = 1, 2, \ldots, M, R_i = E[x(n)x^T(n)|x(n) \in \Omega_i]$ is the auto correlation matrix, and $p_i = E[d(n)x(n)|x(n) \in \Omega_i]$is the cross correlation vector for the i th partition Ω_i from auto correlation matrix and cross correlation vector can be expressed as

$$R_i = E[x(n)x^T(n)] \tag{38}$$

$$p_i = E[d(n)x(n)]. \tag{39}$$

The filter weights in each of the M partitions are given by $w_i = [w_{i,1}, w_{i,2}, \ldots, w_{i,N}]^T$ for $i = 1, 2, \ldots, M$.

The procedure of the HPWS filter is shown as in "Fig. 4" and following details

- The observed image will be partitioned into sub-blocks consisting of 5 by 5 pixels.
- Each block will convert into vector in lexicographic process called observed vector.
- Each observed vector through VQ process to determine the best texture similarity from LBG codebook with hard threshold.
- After determining codebook, the process will select the most appropriate filter for that observed vector.
- After the filter process, All of filter estimated vectors will combine together to reconstruct an image.

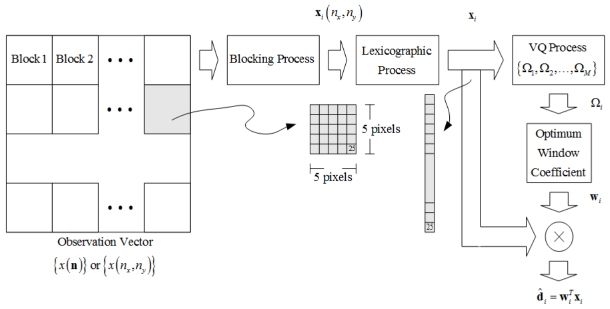

Fig.4: *Imaging system or observation model of HPWS filter [7].*

3.2 Subspace Hard Partition Based Weighted Sum Filter

To reduce the computational complexity of partitioning the R^N observation space, they proposed projecting the observation vectors into R^k subspace ($K < N$) through a linear transformation.

$$\tilde{x}(n) = Ax(n) \tag{40}$$

where A is a $K \times N$ matrix, thus the output of S-HPWS filter can be written

$$F_{S-HPWS}(x(n)) = w^T_{\tilde{p}(\tilde{x}(n))} x(n). \tag{41}$$

where $\tilde{p}(.)$:$R^k \to \{1, 2, \ldots, M\}$.They considered and described three cases for A.

Firstly, A is based on PCA. In this case, the rows of A are made up of the K eigenvectors with the largest values of the covariance matrix for $x(n)$. Second, a simpler method selects K observation sample locations to form the subspace. In this situation, A contains "1" in each row located in a unique column (the other entries are zero). This serves as a simple selection function. Finally, they combine the PCA and center selection method to form the S-HPWS (Center-PCA) method. In the formula, $A = A_{PCA}A_S$, where AS is a $L \times N$ matrix, and $A_{PCA} = K \times L$ PCA subspace transformation matrix, where $K < L < N$. Note that, with the Center-PCA method, they reduce the dimensionality from N to L through center selection method, and then reduce the dimensionality from L to K using PCA.

Note that, we consider on the third case, where A is combine the PCA using the KL transform and center selection method to form the S-HPWS (Center-PCA) method. The procedure of the S-HPWS filter is shown as follow and in "Fig. 5"

- The observed image will be partitioned into sub-blocks and through lexicographic process to covert sub-blocks into observed vector consisting of 51 pixels.
- Each observed vector will reduce its size in PCA process from 51 pixels to 5 pixels.
- Each observed vector through VQ process to determine the best texture similarity from LBG codebook with hard threshold.
- After determining codebook, the process will select the most appropriate filter for that observed vector.
- After the filter process, all of filter estimated vectors will combine together to reconstruct an image.

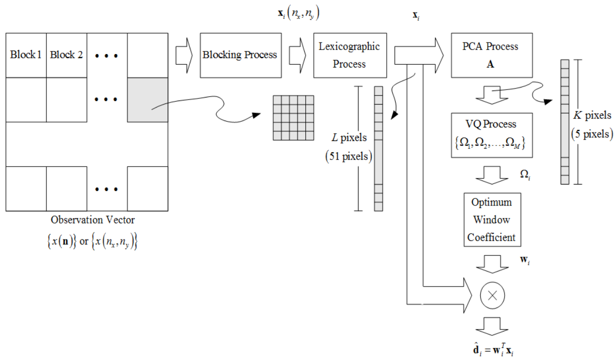

Fig.5: *Imaging system or observation model of S-HPWS filter [7].*

4. SIMULATION RESULTS

To evaluate the performance of the HPWS filter and S-HPWS filter in domain of frequency and spatial, these types of filter are tested and compared using the same set of test images, such as aerial images, human images, miscellaneous images, object images and text images. All the experiments are performed under Windows 7 and MATLAB running on a PC equipped with an Intel Dual-Core CPU at 2.93 GHz and 4 GB RAM memory. The degraded image in restoration application is set as a Gaussian blur together with additive white Gaussian noise (AWGN) with signal to noise ratio (SNR) between 2 to 20 dB encountered versions of the desired image. The sets of training images are used to generate VQ codebook and the training data, which are not one of the sets of training images, are used to determine the weights of HPWS filter and S-HPWS filter of spatial domain.

For frequency domain, we used codebook to determine weight coefficient for each partition.

In practice, we generate codebook of size M from the sets of training images using the LBG algorithm and the codebook for each type of image should be generated once. The HPWS filter and S-HPWS filter in spatial domain have been generated from training data that degraded by Gaussian blur together with additive white Gaussian noise (SNR 20 dB). In frequency domain, the HPWS filter and S-HPWS filter have been generated from codebook that degraded by Gaussian blur together with additive white Gaussian noise (SNR 20 dB). In this simulation, we set codebook size (M) and window moving size (N) of HPWS filter equal to 30 and 25 respectively. For S-HPWS filter, we set $N = 25$ and $K = 5$. In addition, we average the neighborhood pixel of the filter estimated smooth the image.

The codebook of aerial image, which is similar to codebook of human image, object image and miscellaneous image, and the codebook of text image are shown in "Fig.6" and "Fig.7". The partitions of the codebook for aerial image consist of edges and corners at various uniform regions. On the other hand, the codebook for text image does not show the unique feature of text, which offers poor performance when implemented on VQ process.

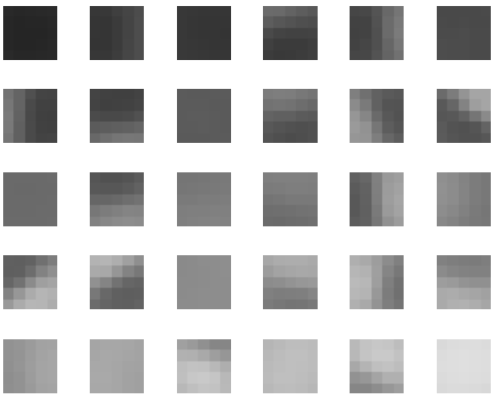

Fig.6: *Codebook for aerial image.*

Table 1: *Comparison of simulation time.*

Time estimated for PWS method (minutes)	Types of image				
	Aerial	Human	Miscellaneous	Object	Text
HPWS (Spatial)	7.30	6.53	8.72	8.98	171.09
S-HPWS (Spatial)	6.35	6.49	8.38	8.83	171.09
HPWS (Frequency)	2.36	3.04	2.59	3.36	160.33
S-HPWS (Frequency)	2.36	3.04	2.59	3.36	160.33

Table 1 shows total computation time of all types of filters which show that both types of PWS filter in frequency domain use less time to restore the degraded version of image.

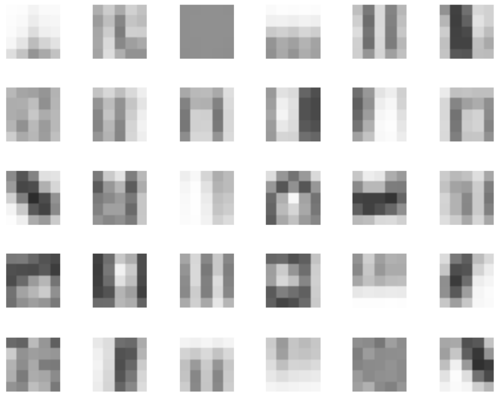

Fig.7: *Codebook for text image.*

From Table2 shows that frequency domain S-HPWS filter is the most successful that required less memory and computation time by used PCA technique to reduce size of data. Due to this size, the complexity of computation is also reduced. Frequency domain PWS filter determine weight coefficient for each partition of codebook. For spatial domain HPWS filter offer good performance to restore image, but not successful in term of memory usage and computation time. Spatial domain PWS filter determine weight coefficient used training data.

Table 2: *Comparison of memory usage.*

Memory usage (Mb)	Types of image				
	Aerial	Human	Miscellaneous	Object	Text
HPWS (Spatial)	48.598	48.598	48.598	48.598	48.598
S-HPWS (Spatial)	46.733	46.733	46.733	46.733	46.733
HPWS (Frequency)	41.719	41.719	41.719	41.719	41.719
S-HPWS (Frequency)	41.300	41.300	41.300	41.300	41.300

The simulation results show that spatial domain HPWS filter offers the best performance when we apply to restore object image, but this filter offers poor performance when we apply to restore miscellaneous image. On the other hand, frequency domain HPWS filter offers good performance when we apply to restore both object image and miscellaneous image. The frequency domain S-HPWS filter offer best performance when we apply to restore miscellaneous image. Nevertheless, all types of filters are failed to reconstruct text image.

For example to illustrate the performance of filters, the observed images are degraded by Gaussian blur together with additive white Gaussian noise with 8 dB of SNR and the filters trained with Gaussian blur together with additive white Gaussian noise with 20 dB of SNR. The desired version, degraded version

Table 3: *PSNR comparison of spatial domain HPWS filter.*

SNR (dB)	Types of image				
	Aerial	Human	Miscellaneous	Object	Text
2	23.772	22.461	17.550	27.144	17.975
4	24.164	23.602	18.943	28.327	18.055
6	24.405	24.440	20.390	29.122	18.108
8	24.570	25.024	21.580	29.730	18.141
10	24.675	25.369	22.373	30.222	18.161
12	24.741	25.591	22.859	30.509	18.175
14	24.783	25.750	23.303	30.820	18.177
16	24.813	25.863	23.614	30.938	18.173
18	24.826	25.927	23.825	31.008	18.174
20	24.839	25.958	23.966	31.073	18.172
22	24.849	25.981	24.085	31.108	18.172

Table 4: *PSNR comparison of spatial domain S-HPWS filter.*

SNR (dB)	Types of image				
	Aerial	Human	Miscellaneous	Object	Text
2	23.090	21.034	13.308	24.050	20.737
4	23.555	22.552	15.224	27.619	21.196
6	23.880	23.700	17.514	28.766	21.424
8	24.119	24.434	19.028	29.601	21.815
10	24.253	24.993	21.533	30.072	21.986
12	24.345	25.313	22.197	30.406	22.081
14	24.4179	25.5240	22.7244	30.6046	22.023
16	24.4459	25.6195	23.1578	30.7196	21.921
18	24.4729	25.6677	23.4438	30.7915	22.177
20	24.4867	25.7093	23.6467	30.8319	21.933
22	24.4932	25.7327	23.8851	30.8811	22.348

Table 5: *PSNR comparison of frequency domain HPWS filter.*

SNR (dB)	Types of image				
	Aerial	Human	Miscellaneous	Object	Text
2	23.151	22.639	22.886	25.433	21.668
4	23.560	23.521	23.819	26.304	22.224
6	23.860	24.171	24.594	27.004	22.153
8	24.042	24.678	25.153	27.524	22.045
10	24.202	25.012	25.498	27.799	22.090
12	24.290	25.257	25.790	28.080	22.375
14	24.303	25.412	25.961	28.161	22.273
16	24.414	25.538	26.141	28.349	22.034
18	24.378	25.562	26.130	28.473	22.369
20	24.397	25.648	26.218	28.455	22.332
22	24.426	25.708	26.220	28.623	22.480

Table 6: *PSNR comparison of frequency domain S-HPWS filter.*

SNR (dB)	Types of image				
	Aerial	Human	Miscellaneous	Object	Text
2	23.122	22.642	22.896	25.430	21.801
4	23.584	23.518	23.822	26.303	21.907
6	23.867	24.174	24.589	27.001	21.880
8	24.102	24.679	25.151	27.521	22.187
10	24.169	25.016	25.503	27.802	22.268
12	24.272	25.257	25.795	28.079	22.289
14	24.294	25.412	25.965	28.157	22.161
16	24.391	25.541	26.140	28.343	21.997
18	24.343	25.561	26.138	28.469	22.281
20	24.392	25.652	26.217	28.451	22.004
22	24.424	25.711	26.221	28.629	22.469

and restored version of images such as aerial image, human image, miscellaneous image, object image and text image are shown in "Fig.8", "Fig.9", "Fig.10", "Fig.11" and "Fig.12" respectively.

5. CONCLUSION

In this paper we have presented a framework of HPWS and S-HPWS filter, both spatial and frequency domain, and evaluated their performance. Spatial domain HPWS filter can be effectively applied on the images, such as object, human and aerial image. For frequency domain of S-HPWS filter, using PCA in order to reduce the computational burden is appropriate in image denoising and debluring application for an image, such as miscellaneous. Nevertheless, all types of filters offer poor performance when we attempt to restore text image.

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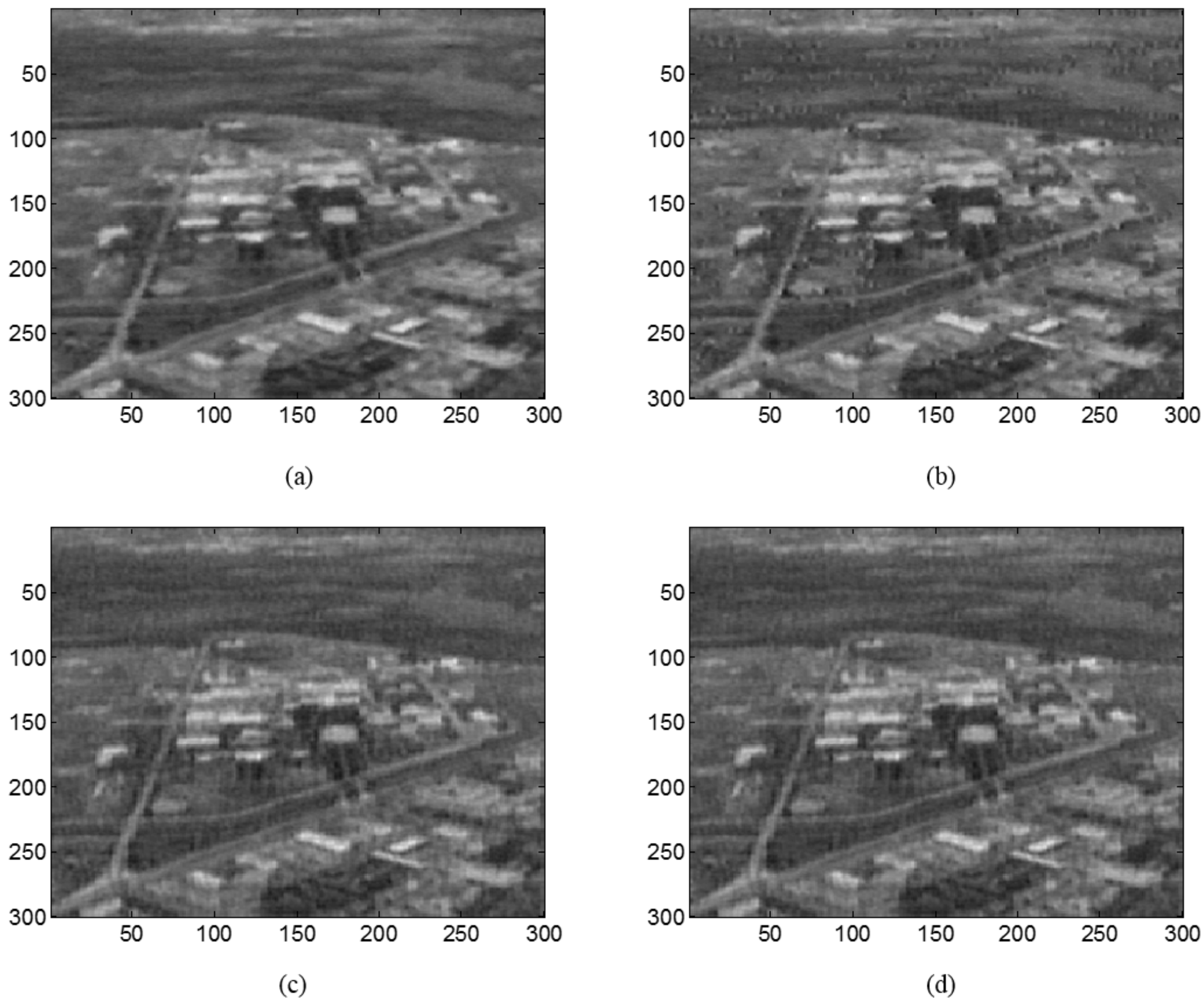
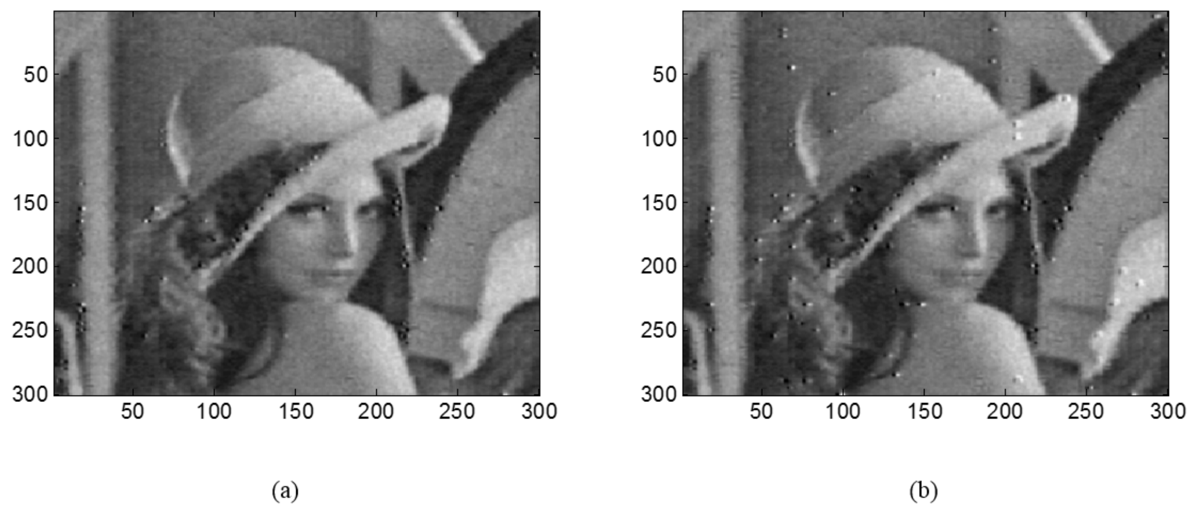


Fig.8: *Estimated filter of aerial image: (a) Spatial domain HPWS filter. (b) Spatial domain S-HPWS filter. (c) Frequency domain HPWS filter. (d) Frequency domain S-HPWS filter.*



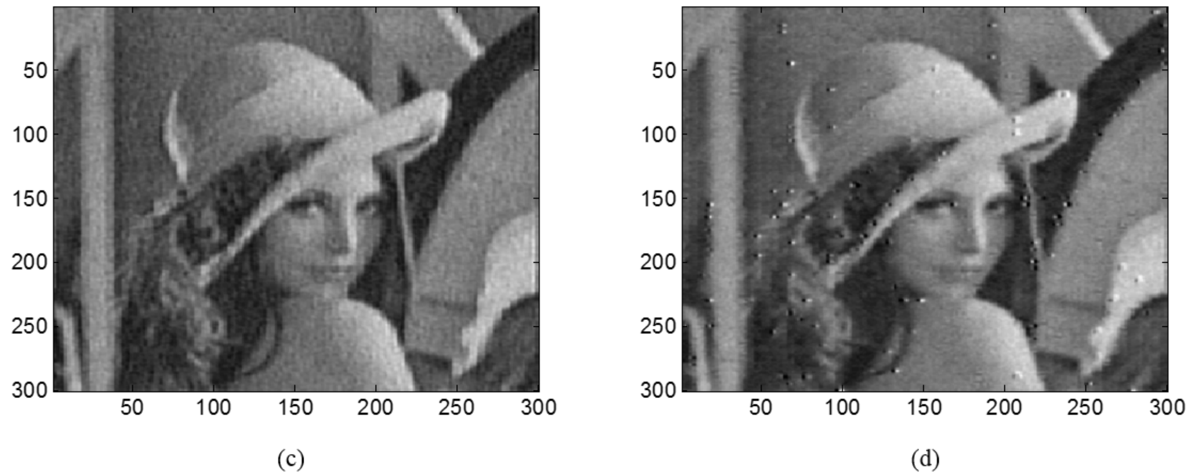


Fig.9: *Estimated filter of human image: (a) Spatial domain HPWS filter. (b) Spatial domain S-HPWS filter. (c) Frequency domain HPWS filter. (d) Frequency domain S-HPWS filter.*

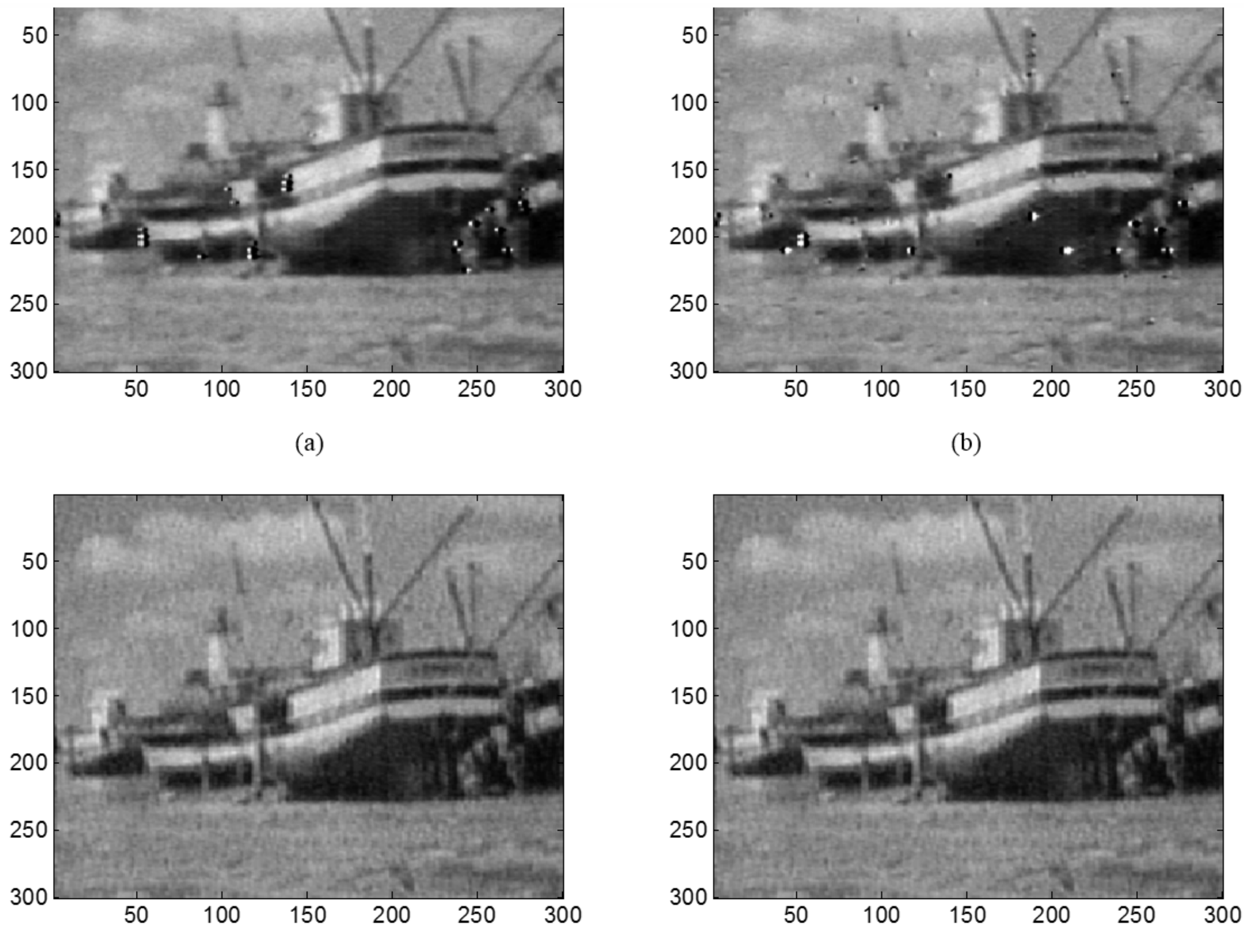


Fig.10: *Estimated filter of miscellaneous image: (a) Spatial domain HPWS filter. (b) Spatial domain S-HPWS filter. (c) Frequency domain HPWS filter. (d) Frequency domain S-HPWS filter.*

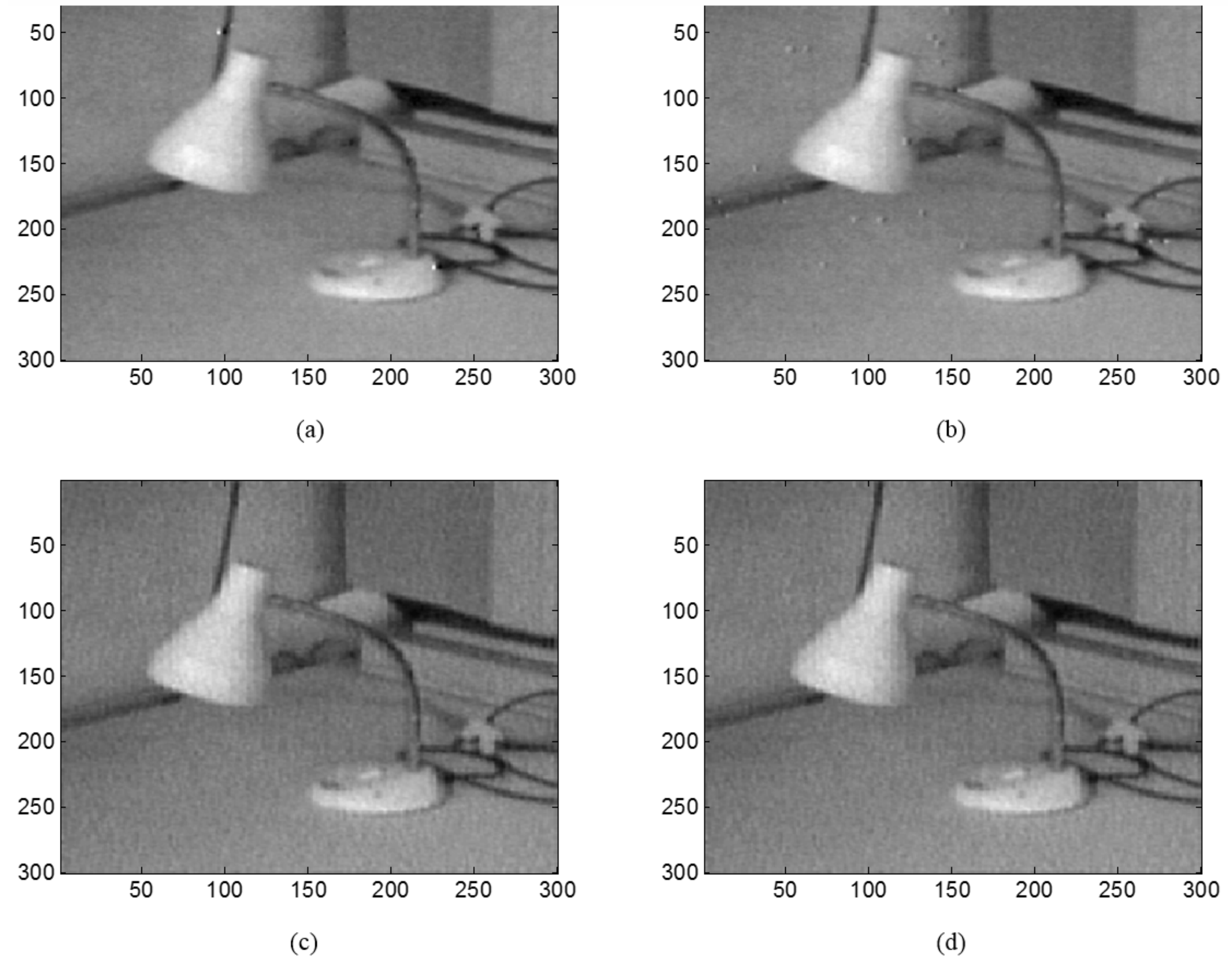
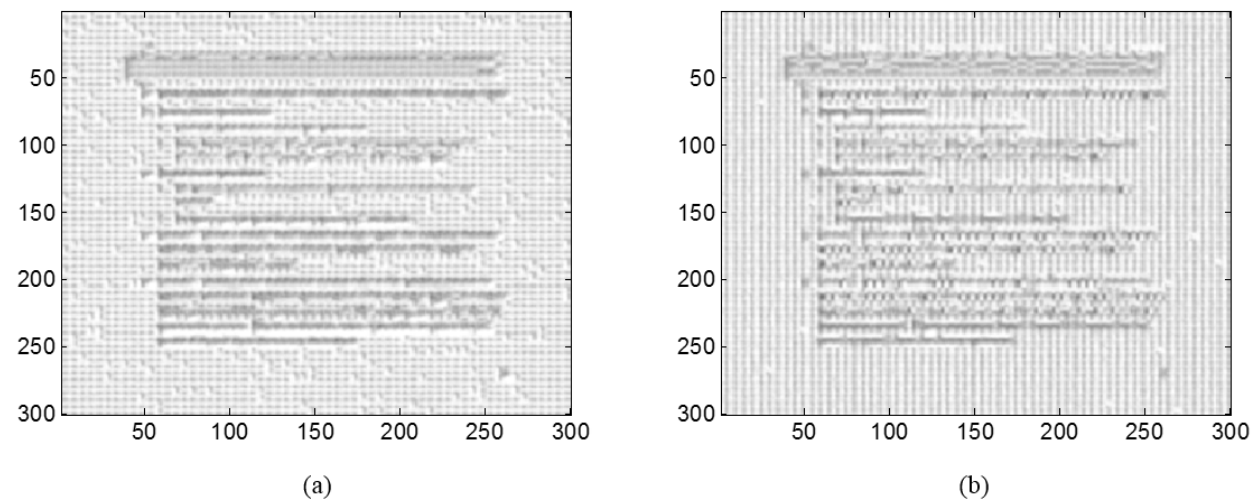
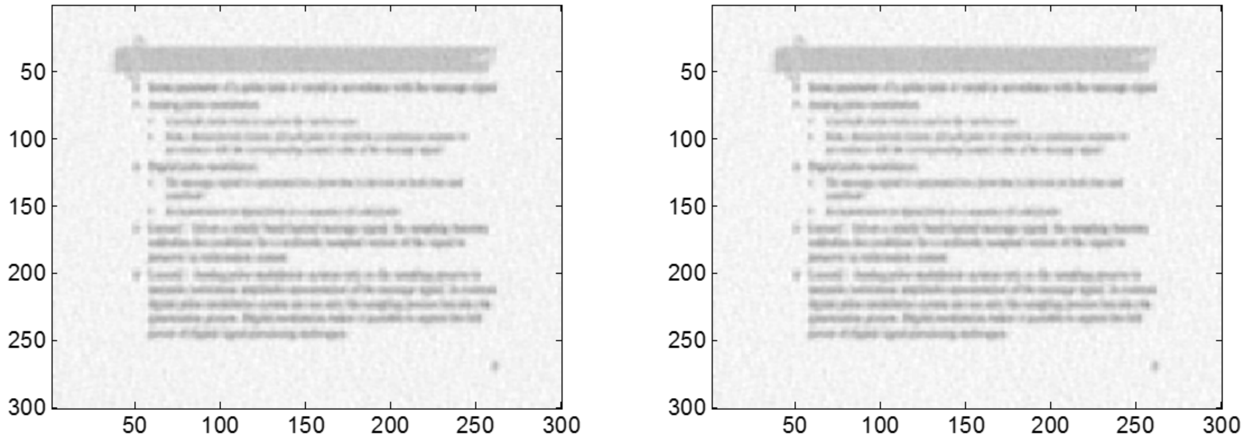


Fig.11: *Estimated filter of object image: (a) Spatial domain HPWS filter. (b) Spatial domain S-HPWS filter. (c) Frequency domain HPWS filter. (d) Frequency domain S-HPWS filter.*





(c) (d)

Fig.12: *Estimated filter of text image: (a) Spatial domain HPWS filter. (b) Spatial domain S-HPWS filter. (c) Frequency domain HPWS filter. (d) Frequency domain S-HPWS filter.*

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