Mixed Noise Parameter Estimation Based on Variance Stable Transform

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Abstract: The ultimate goal of image denoising from video is to improve the given image, which can reduce noise interference to ensure image quality. Through denoising technology, image quality can have effectively optimized, signal-to-noise ratio can have increased, and the original mage information can have better reflected. As an important preprocessing method, people have made extensive research on image denoising algorithm. Video denoising needs to take into account the various level of noise. Therefore, the estimation of noise parameters is particularly important. This paper presents a noise estimation method based on variance stability transformation, which estimates the parameters of variance stability transformation by minimizing the noise distribution peak, and improves the parameter accuracy of mixed peak estimation by comparing and analyzing the changes of parameters. The experimental results show that the new algorithm of noise estimation has achieved good effects, which are making the field of video denoising more extensive.

Keywords: Denoising technology, image quality, signal-to-noise ratio, variance stability.

1 Introduction

With the popularization of various digital products, images and videos are more and more commonly used in our everyday activities. Large amount of object information carried and the main way for people becomes to obtain original information from outside. However, in the process of image acquisition, transmission and storage, images are often degraded by various noises and effects, and image preprocessing algorithms are directly related to the effect of subsequent image processing (such as image segmentation). To obtain high quality, it is necessary to denoise the image to maintain the integrity of the original information and remove the useless information. Therefore, noise reduction is a serious influence on the image quality of video image, which brings great difficulties to the follow-up processing of video image and affects the visual experience of traditional video image [Wen, Ng and Huang (2008); Tang and Jiao (2009); Portilla, Strela and Wainwright (2003)]. Accurate estimation of noise is helpful to improve the performance of

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denoising algorithm and solve the problem of image quality degradation caused by noise interference. The denoising technology can effectively improve the image quality, increase the signal-to-noise ratio, and better reflect the information carried by the original image. As an important means of preprocessing, people have carried out extensive research on image denoising algorithm. Among the existing denoising algorithms, some have achieved good results in low-dimensional signal image processing, but they are not suitable for high-dimensional signal image processing. Either the denoising effect is better, but part of the image edge information is lost, or the research of detecting image edge information is devoted to preserving image details. How to find a better balance between resisting noise and retaining details has become the focus of research in recent years.

The spatial noise estimation algorithm mainly relies on the weak texture region to process the noisy image, which has divided into mixed noise estimation, filter-based noise estimation and image patch-based noise estimation [Liu and Lin (2012)]. Liu et al. [Liu, Tanaka and Okutomi (2012)] obtained the weak texture region by the gradient covariance matrix, and got the level of Gaussian noise by the weak texture. Pei et al. [Pei, Tong, Wang et al. (2010)] processes the texture detail information by adaptive filter, and combines the noise image patch with its filtered image patch to estimate the noise level. Ponomarenko et al. [Ponomarenko, Lukin, Zriakhov et al. (2007)] uses DCT transform to transform the image into the frequency domain, and finally separates the noise to obtain a pure, noise-free image. The above method is easier to obtain noise estimation and obtain a noise-free image when processing some low-pixel images with less texture. Li et al. [Li, Wang, Chang et al. (2011)] proposed wavelet transform to reduce the entropy of the image, and used the relationship between the entropy detection of the noise signal and the variance to estimate the noise. Huang et al. [Huang, Dong, Xie et al. (2017)] proposed to perform an average absolute deviation estimation (MAD) to obtain the estimative standard soft threshold.

In many cases, the image patch texture between the spatial domain and the transform domain is more and rough, and the video image often contains many random texture interferences. The traditional noise estimation algorithm cannot recognize the complex texture video image. The matrix domain noise estimation performs matrix decomposition on the image signal from video and the noise signal, and is suitable for removing the video image of the multi-dimensional texture [Zhu and Milanfar (2010)]. Pyatykh et al. [Pyatykh, Hesser and Zheng (2013)] uses a block-based principal component analysis (PCA) algorithm to process video images with smooth regions, and can obtain accurate noise estimation levels for video images with complex texture regions. Liu et al. [Liu and Lin (2012)] used a singular value decomposition (SVD) based noise estimation algorithm to obtain the noise level. The above noise estimation algorithm is only used to estimate Gaussian noise, and the Poisson-Gaussian noise estimation caused by hardware such as sensors is not ideal.

Based on the above research, this paper proposes a method based on principal component analysis combined with variance stable transform (VST) to achieve image noise estimation. The modified algorithm can not only identify the Gaussian noise estimation caused by hardware, but also estimate the noise evaluation level caused by multi-texture interference. At the same time, this paper in Section 2 introduces Matrix domain based noise estimation, which we can know the noise distribution and mixed noise estimation parameters. Section 3 presents VST based noise estimation, which can get the Variance stable transformation and the parameters of the VST transformation. The experimental results in Section 4 show that the optimized algorithm combining the noise estimation algorithm with the conventional video denoising idea has fast response speed and wider application fields.

2 Matrix domain based noise estimation

2.1 PCA noise estimation

It is assumed that the noise signal is additive white Gaussian noise, and *x*, *n*, *y* represent the original video image, the noise signal, and the noisy video image contaminated by noise, respectively. Then, the number of image patches contained in the noisy image y is N , the calculation formula is as follows:

$$N = (S_1 - M_1 + 1)(S_2 - M_2 + 1) \quad (1)$$

where S_1, S_2 represents the number of columns and rows of the noisy image y , that is, M_1、M_2 represents the size of the image patch. Each image patch is recombined to obtain a vector of size $M = M_1 \times M_2$. Because the noisy image is superimposed by the original video image and the noise signal, *x*, *n*, *y* respectively contain corresponding image patches, and the corresponding vectors are X , N , Y , respectively. Since the noise signal is additive white Gaussian noise, that is, independent of the image signal from video, the original video image and the noise signal satisfy the following relationship:

$$\operatorname{cov}(X, N) = 0 \quad (2)$$

The model of the image patch is known, and then the appropriate image patch is selected for principal component analysis. First, a positive integer m is predefined. When all the image patches x_i corresponding to the original video image x are in the subspace $V_{M-m} \in \mathbb{R}^M$, the information of the original video image x has redundancy. The subspace has a smaller dimension $M - m$ than the vector dimension M . Therefore, we select the required image patches according to this assumption, and select the standard formula as follows:

$$d_i = Dis(x_i, V_{M-m}) \ \ i = 1.......N \quad (3)$$

In the Eq. (3), when the distance is expressed by $Dis(\cdot)$, that is, the distance between the image patch x_i and the subspace $V_{M-m} \in \mathbb{R}^M$ satisfies a certain range, it is determined that the image patch x_i is a suitable image patch. According to the Spearman rank correlation coefficient [Nikolay, Vladimir, Alexander et al. (2009)], it can have concluded that there is a positive correlation between the image patch distance d_i and the standard deviation of the image patch. Therefore, the appropriate image patch can have selected for principal component analysis by calculating the standard deviation to calculate the distance of the image patch.

$$s(x_i)=s(y_i)-\sigma^2 \quad i=1.......N \tag{4}$$

According to the above formula, the noisy image patch y_i is positively correlated with the image patch distance d_i, so that the appropriate image patch can be selected for principal component analysis based on the noisy image patch y_i. After obtaining the image patch model and the appropriate image patch, the noise variance is obtained by principal component analysis. Assume that the sample covariance matrix S_X, S_Y of the vectors X, Y are respectively represented, and the eigenvalue decomposition is performed on S_X, S_Y respectively.

2.2 SVD estimation

The noisy estimation of singular value decomposition is estimated by the singular level, and is mainly divided into three parts. Assume that the noisy video image is y, the original video image is x, and the noise signal is n, which satisfies the following formula:

$$y=x+n \tag{5}$$

(1) Singular value decomposition (SVD): Based on linear algebra, r is a matrix A of rank, it can be decomposed into three different matrices as follows:

$$\begin{aligned} &A=S\times W\times V^T\\ &W^TW=I_{mm}\\ &V^TV=I_{nn} \end{aligned} \tag{6}$$

Where U, S, V denote an orthogonal matrix, a diagonal matrix and another orthogonal matrix, respectively, m, n, I are representing the size of the matrix and the unit square matrix A, respectively. $s(i)(i=0,1,...,r)$ is a singular value, and it has arranged in descending order as follows:

$$s(1)>s(2)>...>...>s(r) \tag{7}$$

(2) Additive Gaussian white noise N analysis: Additive white Gaussian noise has a mean of 0 and a standard deviation of σ, the standard deviation and singular value decomposition (SVD) are expressed as follows:

$$\begin{aligned} &N=U\times S_n\times V^T\\ &\sigma^2=\sum_{i=1}^{r}s_n^2(i) \end{aligned} \tag{8}$$

where $s_n(i)$ represents the singular value of the noise signal. Defined M as the last singular value M of the noise signal, the mean of this singular value M is a function of the standard deviation, expressed as follows:

$$P_M(\sigma)=\frac{1}{M}\sum_{i=r-M+1}^{r}s_n(i) \tag{9}$$

In the above formula, the range of value M is $[1,r]$. When 1 is taken, then only the last eigenvalue satisfies Eq. (9). When it is taken by r, all singular values satisfy this relationship. If the relationship between P_M and σ satisfies a linear relationship, then the following formula holds:

$$\begin{cases} P_M(k\sigma) = k \times P_M(\sigma) \\ P_M(\sigma+\sigma_1) = P_M(\sigma) + P_M(\sigma_1) \end{cases} \tag{10}$$

In the above formula, the standard deviation between the scale factor and the noise signal N_1 is respectively indicated by k, σ_1. Only when the noise signal N_1 has the same distribution for N, that is, the additive white Gaussian noise can obtain a linear relationship. Therefore, it can be obtained that when the process of additive white Gaussian noise is the same, a linear relationship is satisfied with P_M and σ.

When the action of the noise signal is different, the linear relationship between P_M and σ does not apply to all singular values, but a large number of experiments prove that, if M is large enough, it is still linear, P_M and σ the relationship is as follows:

$$P_M(\sigma) = \alpha\sigma, \;\; if \;\; M >> one \tag{11}$$

where α is the slope of the linear function, the degree of linear correlation, related to the choice of M .

In practical applications, the relationship between the last mean value P_M and the standard deviation σ of the noise signal is as follows:

$$P_M = \sum_{i=r-M+1}^{r} s_i = \alpha\sigma + \beta \tag{12}$$

(3) Estimation of noise variance: The noise signal of video image is Gaussian noise N with mean value and standard deviation σ, and noise N_1 has added to the noisy image, and the standard deviation is σ_1, so a new noisy video image is obtained. The standard deviation is $\sqrt{\sigma^2+\sigma_1^2}$ such that the following two formulas are true.

$$P_M = \alpha\sigma + \beta \tag{13}$$

$$P_{1M} = \alpha\sqrt{\sigma^2+\sigma_1^2} + \beta \tag{14}$$

The final noise variance, the expression is as follows:

$$\bar{\sigma} = \frac{\alpha\sigma_1^2}{2(P_{1M}-P_M)} - \frac{P_{1M}-P_M}{2\alpha} \tag{15}$$

The noise estimation in the matrix domain has good noise estimation performance. The noise estimation algorithm of PCA can only deal with Gaussian noise. In addition, It is used in the noise estimation of images, so this paper improves on the basis of this algorithm, it not only can accurately estimate the Gaussian noise level, but also it can be used for the estimation of sensor noise, Gauss-Poisson mixed noise.

3 VST based noise estimation

3.1 Variance stable transformation

Defining the expectation of the random variable, the variance and the standard deviation are $E(\cdot), var(\cdot), std(\cdot)$ respectively, $s^2(\cdot)$ is representing the sample variance, $B(j,k)$ represents the row j and column k element of matrix B. and v^T represents the transpose of vector v. For the original image x, the pixel value $x(q)$ at the position p and the pixel value $y(q)$ of the noisy image y at the point q, there is the following model expression:

$$\begin{aligned} x(q) &= a\lambda(q) \\ y(q) &= a\omega(q) + \sqrt{b}\xi(q) \end{aligned} \tag{16}$$

where $\omega(q) \sim poisson(\lambda(q))$ represents the number of photons, $\sqrt{b}\xi(q) \sim N(0,b)$ is representing the electrothermal noise signal independent of the signal, introduced by the hardware of the sensor. The variance of the noisy image model of Eq. (16) to get the following formula:

$$\text{var}(y(q)) = a^2\lambda(q) + b = ax(q) + b \tag{17}$$

It can be seen that the noise variance is linear with the pixel value of the original image. According to the characteristics of the Poisson distribution, when $\lambda(q)$ is large enough, $\omega(q)$ approximates the mean $\lambda(q)$, distribution with a variance is $\lambda(q)$. Therefore, it can be known from Eq. (16) that the pixel value $y(q)$ of the noisy image approximates the mean distribution is $x(q)$. The pixel value $y(q)$ of the noisy image and the original image pixel value $x(q)$ satisfy the following relationship.

$$y(q) \approx x(q) + \sqrt{ax(q) + b}\xi(q) \tag{18}$$

In order to find the noise level of the noisy image, the noise parameter *a*, *b* has first obtained. Therefore, the noise level problem is transformed into the parameter problem of the noise model.

Defined $f(y(q); a, b)$ as a function of the noisy image.

$$std(f(y(q); a, b)) = \sigma \tag{19}$$

The expression looks is as follows.

$$f(y(q); a', b') \approx f(x(q); a', b') + f'(x(q); a', b')(y(q) - x(q)) \tag{20}$$

According to the expansion formula, the approximate expression of the formula (19) can be obtained as follows:

$$F'(x(q); a', b') \cdot std(y(q)) = \sigma \tag{21}$$

$$F'(x(q); a', b') = \frac{\sigma}{std(y(q))} = \frac{\sigma}{ax(q) + b'} \tag{22}$$

The two sides of the formula (22) are integrated to obtain the following expression:

$$F(\tau;a',b')=\frac{2\sigma}{a'}\sqrt{a'\tau+b'} \tag{23}$$

The random variable is represented by τ , which is a variance stability transformation of a random variable τ .

3.2 PCA-based image patch transformation

It can be seen from the above-described variance stability conversion characteristic that the noise signal of the transformed image $f(y(q);a',b')$ is approximately an additive white Gaussian noise signal with a standard deviation σ. Therefore, there is the following expression.

$$E(f(y(q);a',b'))=Z \tag{24}$$

Defined M as the image patches number of the transformed image, H is the size of the image patch. After removing unnecessary elements of each image patch, the image patch is converted into a vector of size H, where the vector of the transformed image M is $v_1,...v_M$ and the vector of the image Z is $v_1,...v_M$. In order to effectively separate the noise signal from the image signal, assuming that the image z has redundancy, i.e., the dimension of the vector $u_1,...,u_M$ is smaller than H, the PCA is as follows:

1) Calculate the mean vector of the vector $v_1,...v_M$.

$$\bar{v}=\frac{1}{M}\sum_{i=1}^{M}v_i \tag{25}$$

2) Calculate the sample covariance matrix of the vector $v_1,...v_M$, and calculate the formula as follows:

$$S=\frac{1}{M-1}\sum_{i=1}^{M}(v_i-\bar{v})(v_i-\bar{v})^T \tag{26}$$

3) The normalized feature vectors $a_1,...,a_K$ of the sample covariance S are obtained. These feature vectors obey the following relationship:

$$s^2(a_1^T v_i)\ge s^2(a_2^T v_i)\ge\cdots\ge s^2(a_K^T v_i) \tag{27}$$

$s^2(\cdot)$ represents the sample variance.

4) The calculation of the weight $\omega_{k,i}$, the expression is as follows:

$$\omega_{h,i}=a_h^T(v_i-\bar{v}) \tag{28}$$

The range of value k is $[1,H]$, and the range of value i is $[1,M]$. $\omega_{h,i}$ represents the weight k of the center vector $(v_i-\bar{v})$, expressed as ω.

$$s^2(a_i^T v_i) \approx s^2(a_i^T u_i) + \sigma^2 \tag{29}$$

It can be known that the sample variance $s^2(a_k^T v_i)$ is equal to the eigenvalue of the sample covariance matrix S.

If principal component analysis (PCA) utilizes the redundant nature of the no-noise image Z, its sample vector $u_1,...,u_N$ can be represented linearly by the previous eigenvector, and for the last eigenvector, the sample vector $u_1,...,u_N$ is orthogonal. Therefore, the distribution of weight ω_K is the same as the noise distribution [Liu, Tanaka and Okutomi (2012)], so in practice, the distribution of noise signals can be replaced by the distribution characteristic ω_K of the weights. From Eq. (29), in the case of $s^2(a_K^T u_i) = 0$, the noise variance can be approximated as a weight variance, the expression is as follows:

$$s^2(\omega_K) \approx \sigma^2 \tag{30}$$

3.3 VST correction

The noise level of the distribution characteristics with the noise signal must be considered. Since the true value of the noise parameter is unknown, the parameters a'、b' obtained by the VST deviates from the real parameter, we use excessive peaks for detection, and the excess peak calculation for a random variable is as follows:

$$\gamma_Y = \frac{E((Y - E(Y))^4)}{E((Y - E(Y))^2)^2} - 3 \tag{31}$$

For a noise model expression of a noisy image, the noise obeys the sufficient condition of a normal distribution. Defines $x_1 < \cdots < x_M$ as the pixel value of the representation image, the corresponding probability is $h_1,...,h_M$, assuming that the parameters in the VST transformation are $a^{"}, b^{"}$, which are not equal to the real noise model parameters $a^{"}, b^{"}$. The standard deviation $f(y(q); a^{"}, b^{"})$ can have obtained as follows:

$$\begin{aligned} std(f(y(q); a^{"}, b^{"})) &\approx f^{'}(x(q); a^{"}, b^{"}) \cdot std(y(q)) \\ &= \sigma \frac{\sqrt{a' x(q) + b'}}{\sqrt{a^{"} x(q) + b^{"}}} \end{aligned} \tag{32}$$

The noise variance of the pixel value $x_1 < \cdots < x_M$ of the image x can be obtained.

$$\sigma_\tau^2 = \sigma^2 \frac{a x_i + b}{a^{"} x_\tau + b^{"}} \quad \tau = 1,...,M \tag{33}$$

The transformed image $f(z; a^{"}, b^{"})$ obeys a normal distribution with σ_i^2, so in the transformed image $f(z; a^{"}, b^{"})$, its noisy signal can be expressed as a multivariate Gaussian distribution $N(0, \sigma_i^2)$ with weights h_i.

$$\gamma = 3\frac{\sum_{i=1}^{M} h_i \sigma_i^4}{(\sum_{i=1}^{M} h_i \sigma_i^2)^2} - 3 \tag{34}$$

From Eq. (34), the excessive peak is a non-negative number, and only zero if all parameters σ_i are the same, when $a^{"}, b^{"}$ is proportional to the corresponding value $\odot a$、$\odot b$.

$$\frac{\odot a}{a^{"}} = \frac{\odot b}{b^{"}} \tag{35}$$

$f(x(q); a^{'}, b^{'})$ is independent of the original image pixel value $x(q)$, that is, the noisy signal $f(x(q); a^{'}, b^{'})$ is white Gaussian noise. Assume that the sample has an excessive peak value is $G(X_i)$ and the corresponding sample variable is $X_1, ..., X_N$. If $X_1, ..., X_N$ obeys a normal distribution, the sample value $G(X_i)$ multiplied by a coefficient.

$$G(X_i)\sqrt{NO./24} \sim N(0,1) \tag{36}$$

The above equation expresses a certain threshold T_γ, and if $G(X_i)\sqrt{NO./24}$ is a normal distribution by less than the threshold, where the threshold T_γ is non-negative.

It can be known from the above-described detected noise distribution characteristics that the parameters a, b are converted and converted into functions of the parameters σ, ϕ. The expression is as follows:

$$\begin{aligned} a &= \sigma^2 \cos\phi \\ b &= \sigma^2 \sin\phi \end{aligned} \tag{37}$$

Among them, the parameter σ is a non-negative number, and the parameter ϕ has a value range of $[0, \pi/2]$. The following formula is as follows:

$$\begin{aligned} &\frac{\cos\phi}{\cos\phi^{'}} = \frac{\sin\phi}{\sin\phi^{'}} \\ &\Leftrightarrow \sin(\phi - \phi^{'}) = 0 \\ &\Leftrightarrow \phi = \phi^{'} \end{aligned} \tag{38}$$

We can get the calculation as follows.

$$\begin{aligned} f(\tau; a, b) &= f(\tau; \sigma^2 \cos\psi, \sigma^2 \sin\psi) \\ &= \frac{2\sigma}{\sigma^2 \cos\psi}\sqrt{\tau\sigma^2 \cos\psi + \sigma^2 \sin\psi} \\ &= \frac{2}{\cos\psi}\sqrt{\tau\cos\psi + \sin\psi} \end{aligned} \tag{39}$$

From the above equation, VST transform has only related to the parameters ψ, so by repeated iterations, the calculated excessive peak is compared with a given threshold. Finally, the estimated values a', b' of the noisy model parameters are obtained, and then the noise variance of each gray value $\sigma_i^2\ i=0,...,255$ is obtained according to the noisy model.

$$\sigma_i^2 = a^{'}i + b^{'}\ i=0,...,255 \tag{40}$$

According to the above formula, the noisy variance of final average has obtained as the noise variance value. The expression is as follows:

$$\sigma_{avg}^2 = \frac{1}{256}\sum_{i=0}^{255}\sigma_i^2 \tag{41}$$

Therefore, the optimized method proposed in this paper can accurately estimate Gaussian noise and mixed noise, and it has not affected by camera hardware and video image texture. The test results are more stable than the PCA estimates.

4 Test results

This paper verifies the effectiveness of the noise estimation method in the optimized algorithm, and selects four groups of video such as akiyo, supervisor, salesperson, and football [Xiao, Li, Jiang et al. (2015)]. The estimation effects of Gaussian noise or Poisson-Gaussian noise are compared. The error of the noise estimate is defined as $\Delta(\sigma)=|\hat{\sigma}-\sigma|$. This article measures the accuracy of noise estimation by estimating the error of each algorithm. The algorithm-running environment is Windows 7, CPU-Intel Core I 7-2300 K, clocked at 4.70 GHz, and memory is 4 GB, 64 bit. The 5th frame of the test video is compared. The third frame of the four sets of noise-free video sequences is as follows:

(a) akiyo (b) foreman (c) salesman (d) football

Figure 1: The third frame of original video

(1) The error comparison results of added noisy Gaussian are shown in Tab. 1:

Table 1: Comparison of Gaussian noise estimation error

σ	Algorithm	akyio	foreman	salesman	football
10	PCA	0.1600	0.0039	0.0100	0.1375
	Literature [6]	0.0951	0.0364	0.1129	0.3632
	proposed algorithm	0.0532	0.3018	0.0913	0.0321
20	PCA	0.2643	0.2683	0.1719	0.0188
	Literature [6]	0.3327	0.1216	0.3731	0.1832
	proposed algorithm	0.0431	0.0856	0.0526	0.0514
30	PCA	0.8385	0.0178	0.1732	0.0985
	Literature [6]	0.7271	0.2519	0.3681	0.2106
	proposed algorithm	0.6213	0.3287	0.1326	0.4249

It can be seen from Tab. 1, the case of simply adding Gaussian noise, the difference between the noise estimation and the real noise variance estimated is small, and in most cases estimated the noise level by comparing the two methods.

(2) The results of error comparison when the parameters are added Poisson-Gaussian noise have shown in Tab. 2.

Table 2: Comparison of Gaussian-Poisson noise estimation error

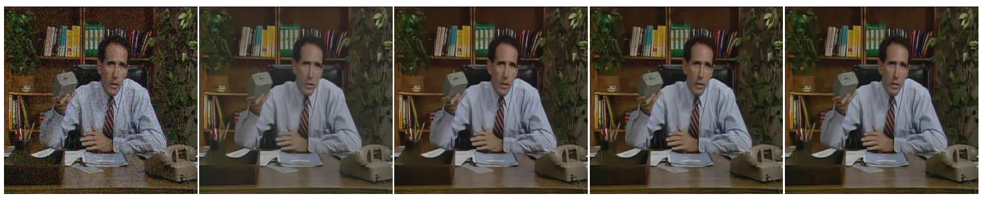
$a/b/\sigma_{avg}$	algorithm	akyio	foreman	salesman	football
5/5/25.739	PCA	15.0540	13.1872	8.7416	10.6535
	Literature [6]	4.1080	7.4630	1.2097	1.5402
	proposed algorithm	0.1395	0.1652	0.3735	0.4257
5/10/27.156	PCA	13.3487	11.2435	7.7648	10.5201
	Literature [6]	4.0269	7.0491	1.1198	0.9475
	proposed algorithm	0.1856	0.5385	0.1042	0.3462
10/5/36.055	PCA	21.5333	20.3788	14.8848	16.4083
	Literature [6]	5.8594	10.5698	1.2330	1.8694
	proposed algorithm	0.2569	0.1438	0.6353	0.5261
10/10/37.080	PCA	21.0025	19.0014	13.3717	15.7649
	Literature [6]	6.2379	10.0850	1.2147	1.8665
	proposed algorithm	0.4185	0.6032	0.2185	0.4871

From the comparison of Tab. 2, by introducing Gauss-Poisson mixed noise, the average variance obtained by the noise estimation algorithm is very close to the average variance of the actual noise, and the accuracy of the comparison algorithm is better. Especially for the PCA noise estimation algorithm has significant accuracy. According to the above comparison results, the noise estimation algorithm can obtain relatively accurate noise level, which can not only accurately estimate simple Gaussian noise, but also obtain more accurate results of Gaussian-Poisson mixed noise. Therefore, the noise estimation algorithm in this paper has good applicability. In order to test and verify the effect of the Text Algorithm, a space-time joint filtering algorithm based on three-dimensional block matching (VBM3D) [Dabov, Foi and Egiazarian (2007)] is combined with the noise estimation (VBM3D+est). Compared with the accelerated near-end gradient method (APG) [Ji, Liu, Shen et al. (2010)], VBM3D algorithm, and dual-domain filtering algorithm (DDID) [Knaus and Zwicker (2013)], Gaussian noise and Gauss-Poisson noise have added to the original video for comparison. The comparison effect is as follows.

(1) Gaussian noise is added, the average value is zero, and the standard deviation is 20. The noise reduction effect of each algorithm is shown in Figs. 2-5.

(a) Noisy video (b) APG (c) DDID (d) VBM3D (e) VBM3D+est

Figure 2: Subjective effect of "akiyo" noise reduction



(a) Noisy video (b) APG (c) DDID (d) VBM3D (e) VBM3D+est

Figure 3: Subjective effect of "salesman" noise reduction

(a) Noisy video (b)APG (c) DDID (d) VBM3D (e) VBM3D+est

Figure 4: Subjective effect of "foreman" noise reduction

(a) Noisy video (b) APG (c) DDID (d) VBM3D (e) VBM3D+est

Figure 5: Subjective effect of "football" noise reduction

Adding a Gaussian white noise with an average value has a standard deviation of 20, from the comparison results of the noise reduction in the above figure, it can be seen that the image brightness after noise reduction by the APG algorithm is generally reduced, and the picture is blurred. The DDID algorithm has a high brightness, and the details are well preserved, but the picture has some oil painting and can only have used for image denoising, which has certain limitations. The VBM3D algorithm also has better brightness, but ringing and blockiness distortion occur. Finally, the processing result of the algorithm is not only better in brightness, but also better in detail. Compared with the VBM3D algorithm, the ringing and blockiness distortions are optimized, and noise estimation has added, and the application range is wider.

(2) Add Gauss-Poisson mixed noise, and compare the noise reduction algorithms as follows:

(a) Video with Noise (b) APG (c) DDID (d) VBM3D (e) VBM3D+est

(a) Video with Noise (b) APG (c) DDID (d) VBM3D (e) VBM3D+est

Figure 6: Effect of Poisson-Guassian mixture noise reduction using parameter 5,5

(a) Video with Noise (b) APG (c) DDID (d) VBM3D (e) VBM3D+est

Figure 7: Effect of Poisson-Guassian mixture noise reduction using parameter 10,5

In Figs. 6-7, when the Poisson-Gaussian noise mixed noise is added, the comparison algorithms APG, DDID and VBM3D noise reduction algorithms do not know the noise level. Therefore, the artificial setting makes the image after noise reduction too smooth, as shown in Fig. 6, or the noise reduction is not complete, and a large amount of noise is reserved. However, the algorithm of this paper obtains the noise level according to the noise estimation and then performs noise reduction, and the obtained noise image has better effect.

This paper adopts PSNR and SSIM [Zhang, Yu, Ding et al. (2013)] as objective indicators of noise reduction. The comparison results are as follows:

Table 3: Objective comparison of the algorithm with APG, DDID and VBM3D

Noise level (a/b)	Algorithm	akyio	foreman	football	malesman
0/20	APG	26.665/0.894	24.370/0.836	25.407/0.795	26.330/0.827
	DDID	34.547/0.916	32.890/0.864	30.153/0.876	31.152/0.879
	VBM3D	34.601/0.914	32.490/0.855	30.221/0.871	31.249/0.876
	proposed algorithm	34.532/0.914	32.347/0.834	30.002/0.854	31.060/0.862
5/5	APG	26.017/0.884	23.246/0.805	24.680/0.760	26.303/0.798
	DDID	32.680/0.891	30.284/0.824	28.423/0.758	29.556/0.800
	VBM3D	32.755/0.907	29.971/0.829	28.696/0.800	30.370/0.854
	proposed algorithm	32.823/0.902	30.021/0.832	28.811/0.807	30.573/0.861
10/5	APG	24.951/0.824	21.964/0.758	23.954/0.713	25.768/0.774
	DDID	28.873/0.814	26.727/0.748	26.960/0.776	28.529/0.790
	VBM3D	30.143/0.837	27.209/0.760	27.2580.781	29.397/0.827
	proposed algorithm	30.625/0.882	27.511/0.800	27.213/0.752	29.085/0.813

From the objective indicators in Tab. 3, by adding pure Gaussian noise, the difference between the proposed algorithm and the comparison algorithm DDID and VBM3D is small, which is obviously better than the APG noise reduction algorithm. When adding Poisson-Gaussian mixed noise, the optimized method is obviously better than the contrast method, and the noise reduction effect is excellent.

5 Conclusion

With the development of science and technology and the need of work and life, the application of digital image filtering will be more and more extensive, and the requirements will be higher and higher. So far, there are still many new ideas and methods in denoising, and constantly enrich image denoising methods. Moreover, the research scope of noise is also expanding, from Gaussian noise to non-Gaussian noise. Denoising technology has a wide range of applications and research prospects, and the research field is constantly expanding. Noise interference has puzzled by video image acquisition, which affects the accuracy of recognition.

This paper is a brief introduction to image denoising technology. In this paper, image-denoising technology is summarized, including the concept of noise and denoising principle, and some basic image denoising methods are introduced. The optimized noise estimation method is proposed for the above phenomena and actual needs by PCA and variance stable transform. In addition, the innovative concept of introducing excessive noise peaks in this paper greatly improves the precision of noise estimation by judging the proportion of noise distribution. This paper estimates the VST transform parameters by the excessive peak minimization, the optimized noise estimation can better obtain the denoising effect and suppress the interference of hardware, which can be widely used in actual production in the future.

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