New Distortion Measure for Vector Quantization of Image

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Abstract: In vector quantization (VQ), mean squared difference (MSD) is a widely used distance measure between vectors. But the distance between the means of each vector elements appears as a dominant quantity in MSD. In the case of image vectors, the coincidence of edge patterns is also important when the human visual system (HVS) is considered. Therefore, we propose a new distance measure that uses the variance of differences to encode vectors and to design codebooks. It can choose more proper codewords to reduce edge degradations and make a useful codebook, which has lots of various edge codewords in place of redundant shades.

1. Introduction

VQ has been widely used in image coding fields because of its good performances even at low bit rates [1][2]. And MSD has been used generally as a distance measure between two vectors, image blocks, to design codebooks and to encode vectors with the designed codebook. Because this measure implies the energy of the difference between vectors, the minimum MSD value is regarded as the optimal minimum distance [3].

But the difference between averages of each vector elements becomes the major part of this energy and that between edge patterns makes relatively small energy. So the edge pattern of the original block can hardly be reserved after VQ. Although the reconstructing capability for smooth region (shade) blocks which occur more frequently than edge region blocks is very important considering the overall picture MSD, degradations in edge parts of an image bring the subjective picture quality down regarding HVS [4][5].

In this paper, a new distance measure is proposed to overcome this drawback of MSD. We determined the variance of differences between vectors as a criterion of edge matching at first and made a new measure by summing this variance of differences and the squared difference of means, so called VDDM, with a decided weighting. By varying this weighting, the ability of edge reconstruction can be controlled to fit the image use's demands. Reconstructed images show that edge degradations can be reduced properly with a little low PSNR (peak signal-to-noise ratio) at an appropriate weighting. VDDM was applied further to the codebook design method, the generalized Lloyd algorithm (GLA) [6] instead of MSD and we could observe that the number of redundant shade codewords is reduced and various edge codewords are generated. So even the performance of PSNR can improved by this efficient codebook.

2. Distortion measures for image vectors

MSD between two K-dimensional vectors, X and Y, is defined as follows.

$$\begin{aligned} D_{MSD}[\mathrm{X}, \mathrm{Y}] &= E[\|\mathrm{X}-\mathrm{Y}\|^2] = E[(\mathrm{X}-\mathrm{Y})^t(\mathrm{X}-\mathrm{Y})] \\ &= \frac{1}{K}\sum_{k=1}^{K-1}(x_k - y_k)^2 \end{aligned} \tag{1}$$

This represents the average energy of the difference between elements of each vector. Performing vector quantization for an image vector is the process of reducing the redundancies in it because the pixel values in a block can not be changed suddenly. It means that this energy includes the difference between means of two vectors as many as the number of vector dimension repeatedly. And the energy from the difference of rest edge patterns takes small parts relatively although they usually have much information because of their random variation. Consequently, MSD is not an appropriate distance measure to design codebooks and to encode image vectors when we consider HVS that is sensitive to the degradation of edge regions.

As a distance measure that compares genuine edge patterns of two blocks except means, the variance of difference is

$$D_{VD}[X,Y] = V[X-Y] = \frac{1}{K}\sum_{k=0}^{K-1}\{(x_k - y_k) - E[X-Y]\}^2 \tag{2}$$

Where $V[.]$ is the variance of a vector. If the edge patterns of each vector are quite different, the difference elements between corresponding vectors will have eventful values and this value will be large. So we can decide how much edge patterns are similar to each other using this measure. Equation (2) becomes

$$\begin{aligned} D_{VD}[X,Y] &= \frac{1}{K}\sum_{k=0}^{K-1}(x_k - y_k)^2 - \{E[X-Y]\}^2 \\ &= E[(X-Y)^t(X-Y)] - \{E[X-Y]\}^2 \\ &= D_{MSD}[X,Y] - \{E[X-Y]\}^2 \end{aligned} \tag{3}$$

This shows that the variance of differences is the quantity removed mean of differences from MSD.

To test this measure, several edge patterns are made by two gray levels shown in Figure 1. Distances using MSD between the pattern (a) and patterns (b), (c), and (d) each are the same. But the pattern (c) is the closest pattern to (a) when the variance of difference is used. Clearly, it can be seen that they are also the closest patterns by our eyes and it means that variance of difference is more appropriate distance measure for edge pattern matching.

The variance of differences can reconstruct only the edge patterns without consideration of mean values and additional computations for the distance of means are necessary. So we combine this variance of differences and the squared difference of means of two vectors linearly to use for common images. Here is the new measure, VDDM:

$$\begin{aligned} D_{VDDM}[X,Y] &= D_{VD}[X,Y] + \alpha\{E[X] - E[Y]\}^2 \\ &= D_{VD}[X,Y] + \alpha D_{DM}[X,Y] \end{aligned} \tag{4}$$

As the weighting α is lessened from 1 to 0, the portion of distance between edge patterns becomes larger than that of means between vectors.

When $\alpha = 1$, this is

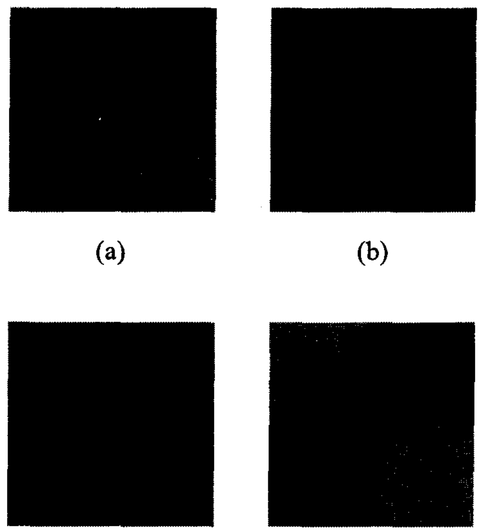
$$\begin{aligned} D_{VDDM}[X,Y] &= D_{VD}[X,Y] + \{E[X] - E[Y]\}^2 \\ &= D_{VD}[X,Y] + \{\frac{1}{K}\sum_{k=0}^{K-1}x_k - \frac{1}{K}\sum_{k=0}^{K-1}y_k\}^2 \\ &= D_{VD}[X,Y] + \{\frac{1}{K}\sum_{k=0}^{K-1}(x_k - y_k)\}^2 \\ &= D_{VD}[X,Y] + \{E[X-Y]\}^2 \\ &= D_{MSE}[X,Y] \end{aligned} \tag{5}$$

Note that it becomes the same value as MSD. It is controllable to choose the codeword from with the optimal minimum distance to suitable for human visual system according to alternating the weighting α.

We substituted equation (3) to (4), and get

$$\begin{aligned} D_{VDDM}[X,Y] &= D_{VD}[X,Y] + \alpha\{E[X] - E[Y]\}^2 \\ &= D_{MSD}[X,Y] - (1-\alpha)\{E[X-Y]\}^2 \end{aligned} \tag{6}$$

It shows that this measure can be calculated MSD and additional two multiplications.



(a) (b)

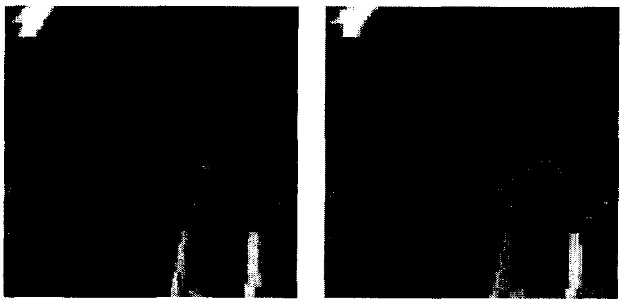
(c) (d)

Figure 1. Comparison of MSD and the variance of differences between several edge pattens made by two grey levels; (a) reference pattern [135,119], (b) MSE 64, VD 64 [127,127], (c) MSE 64, VD 0 [143, 127], and (d) MSE 64, VD 64 [143,111].

3. Vector quantization using VDDM

PSNR (peak signal-to-noise ratio) has been generally and almost solely used as a objective criterion to test the quality of the reconstructed image in the field of image coding. But because it comes from the total MSD between original and reconstructed images, the biggest value is obtained when an image is encoded with $\alpha = 1$ in VDDM and it decreases as the α goes smaller. It shows that PSNR hardly appreciates the subjective image qualities such as the capability of the edge reconstruction.

When VDDM is applied to encoding images with the codebook designed by the conventional MSD based method, good subjective picture qualities are achieved without uncomfortable degradations in other regions, that classified into shade or midrange parts, at the range that α is from 0.6 to 0.8. Figure 2 illustrates edge regions of two test images reconstructed by MSD and VDDM with α=0.6 each. Of course, the same codebook is used. Characters and edges of the second test image are shown more apparently than the first one.

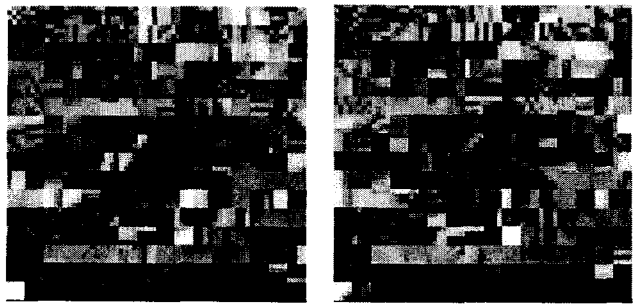


(a) (b)

Figure 2. Enlarged test images encoded using (a) MSE and (b) distance measure using VD ($\alpha = 0.7$).

About two of third of segmented blocks in general images are known as non-edge blocks and edge patterns of this scanty edge blocks come out irregularly [4][5]. This plentiful shade blocks greatly contribute to the designed codebook. Moreover, as MSD has been used as a distance measure in the previous codebook design method, the clusters of training image blocks that are going to be codewords are made by the means of each blocks. A number of shade codewords classified precisely are generated and some edge codewords are survived. This reason can make the PSNR of the reconstructed image down because the codebook cannot supply the proper codewords to specified edge patterns that occurs at times.

It can be possible that this problem will be improved by using VDDM in the codebook design. We can prove this fact by the picture of the designed codebooks using the previous and the proposed distance measures each that are shown in Figure 3.



(a) (b)

Figure 3. The designed codebooks using (a) MSE and (b) distance measure using VD (α = 0.8).

4. Simulation and results

Five 512×512 size images, Baboon, Barbara, Bank, Pepper, and Woman are used to design codebook. At first, we generate a codebook that has the size of N = 256 by the conventional method, GLA with MSD. For both test images Lena and Boat, the maximum PSNR values come out at the point that α = 1, MSD, and edge reconstruction are improved when α is less than 1 as we expected.

VDDMs at α = 0.8 and 0.6 are applied to codebook design as distortion measures and PSNR results about Lena are illustrated in Figure 4. The value in cases of $\alpha = 0.8$ are higher than that of MSD on the whole because it could make an efficient codebook that has various edge codeword in place of a lot of redundant shade codewords. But as α goes more lower such as 0.6, too much edge codewords are generated in the codebook and being short of shade codewords make PSNR down again.

In table 1, variations of PSNR brought about by changing codebook size N for two design cases of MSD and VDDM with α = 0.8 are shown. When the size is large and α at encoding process is closed to 1, it becomes the highest value and the codebooks designed with α = 0.8 are more efficient than MSD without relation to codebook sizes. And table 2 gives the result that was obtained from encoding Lena and Boat using MSD, and VDDM with α = 0.6, 0.7, and 0.8 by codebooks designed using MSD, α = 0.6, and 0.8 each. We paid attention to the fact that the PSNR designed and encoded by MSD and the ratio designed at α

= 0.8 and encoded at $\alpha = 0.7$ have almost equal PSNR for two images, and can see that the performance of reconstruction for edge regions are improved in the latter case.

5. Concluding Remarks

VDDM is proposed to reserve the edge pattern that is important to HVS because MSD, mainly used for distortion measure for VQ, tends to be determined by the difference of vector means. It is made by the variance of differences and the difference of means between vectors with a weighting. When it is used for VQ, the degradations of edge regions in the reconstructed images can be reduced and the designed codebook become efficient for various edge pattern codewords.

In VDDM, it is possible that the grade of the edge reconstruction can be controlled to fit the image use by varying the weighting value. It equals with MSD when the weighting is 1, and when the weighting is less or greater than 1, then mean value or edge pattern is emphasized. Therefore this measure can be used diverse fields such as medical image coding, edge detection, and pattern matching as well as general image coding.

References

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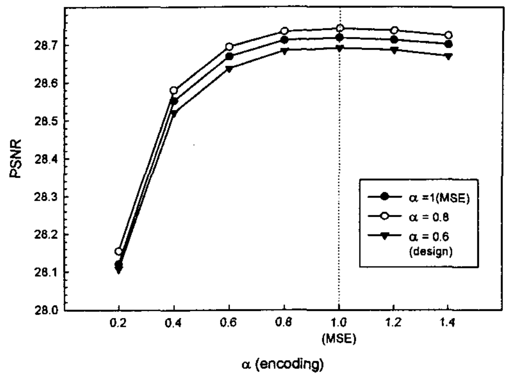

Figure 4. Relations between α and PSNR in encoding by codebooks designed using VDDM.

Table 1. PSNR comparisons with variation of codebook size N.

Design	MSE			α =0.8		
Case / N	MSE	α =0.8	0.6	MSE	α =0.8	0.6
4	22.27	22.27	22.27	22.27	22.27	22.27
16	25.25	25.25	25.22	25.29	25.28	25.26
64	27.10	27.09	27.06	27.13	27.12	27.09
128	27.98	27.98	27.93	28.01	27.99	27.95
256	28.72	28.71	28.67	28.74	28.73	28.69
512	29.25	29.24	29.19	29.28	29.27	29.23

Table 2. PSNR comparisons with variation of α in codebook design and encoding.

Encoding / design	Lena				Boat			
	MSE	$\alpha = 0.6$	0.7	0.8	MSE	$\alpha = 0.6$	0.7	0.8
MSE	28.72	28.67	28.69	28.71	29.37	29.32	29.34	29.36
$\alpha = 0.6$	28.69	28.64	28.67	28.68	29.29	29.22	30.26	30.28
$\alpha = 0.8$	28.74	28.69	28.72	28.73	30.39	30.33	30.36	30.38