A FAST VECTOR QUANTIZATION IMAGE ENCODING USING TCHEBICHEF MOMENTS

Spiridon Florin Beldianu
"Gh. Asachi" Technical University of Iasi, Faculty of Electronics and Telecommunications,
Bd. Carol 11, Iasi , 700506, Romania, fbeldianu@etc.tuiasi.ro

Abstract—The codeword searching sequence is sometimes vital to the efficiency of a VQ encoding algorithm. In this paper, we present a fast encoding algorithm for vector quantization that uses Tchebichef moments of an image block three characteristics of a vector: linear projection, variance and third moment. A similar method using linear projection and variance of an image block was already proposed (EENNS, IEENNS). Severeal new inequalities based on Tchebichef moments of a image block are introduced to reject those codewords that are impossible to be the nearest codevector and cannot be rejected by inequalities based on sum and variance, thereby saving a great deal of computational time, while introducing no extra distortion compared to the conventional full search algorithm. The simulation results confirm the effectiveness of the proposed algorithm compared with improved equal-average equal-variance nearest neighbor search (IEENNS).

Keywords—Fast nearest neighbor search, image vector quantization

INTRODUCTION

Vector Quantization (VQ) [1], [2] is an efficient technique for data compression and has been successfully used in various applications involving VQ-based encoding and VQ-based recognition. The response time of encoding and recognition is a very important factor to be considered for real-time applications. The k -dimensional, N -level vector quantizer is defined as a mapping from a k -dimensional Euclidean space into a certain finite set $C = \{C_1, C_2, ..., C_N\}$. The subset C is called a codebook and its elements are called codewords. The codeword searching problem in VQ is to assign one codeword to the input test vector in which the distortion between this codeword and the test vector is the smallest among all codewords. Given one codeword $C_j = (c_{j1}, c_{j2}, ..., c_{jk})$ and the test vector $\mathbf{x} = (x_1, x_2, ..., x_k)$, the squared Euclidean distortion measure can be expressed as follows: $D(C_j, \mathbf{x}) = \sum_{i=1}^{k} (c_{ji} - x_i)^2$.

From the above equation, each distortion calculation requires k multiplications and $2k-1$ additions. For an exhaustive full search algorithm, encoding each input vector requires N distortion computations and $N-1$ comparisons. Therefore, it is necessary to perform kN multiplications, $(2k-1)N$ additions and $N-1$ comparisons to encode each input vector. The need for a larger codebook size and higher dimension for high performance in VQ encoding system results in increased computation load during the codeword search.

Many researchers have looked for fast encoding algorithms to accelerate the VQ process. These works can be classified into two groups. The first group rely on the use of data structures that facilitate fast search of the codebook such as TSVQ or K-d tree [3] ,[4]. The second group addresses an exact solution of the nearest-neighbor encoding problem. A very simple but effective method is the partial distortion search (PDS) method reported by Bei and Gray [5], which allows early termination of the distortion calculation between a test vector and a codeword by introducing a premature exit condition in the searching process. The equal-average nearest neighbor search (ENNS) algorithm uses the mean value of an input vector to reject impossible codewords [6]. The improved algorithm, i.e., the equal-average equal-variance nearest neighbor search (EENNS) algorithm, uses the variance as well as the mean value of an input vector to reject more codewords [7]. This algorithm reduces computational time further with $2N$ additional memory. The improved algorithm termed IEENNS uses the mean and the variance of an input vector like EENNS but develops a new inequality between these features and the distance [8].

In this paper, we will examine IEENNS algorithm which uses two inequalities between mean, variance and the distance and we present an algorithm based on Tchebichef moments.

THE ALGORITHM

The IEENNS algorithm [7] use two characteristics of a vector, sum and the variance simultaneously. Let $\mathbf{x} = [x_1, x_2, ..., x_k]$ be a k-dimensional vector. The sum of vector components can be expres as $S_{\mathbf{x}} = \Sigma_{i=1}^{k} x_i$ and the variance as $V_{\mathbf{x}} = \sqrt{\Sigma_{i=1}^{k}(x_i - S_{\mathbf{x}}/k)}$. Assuming the curent minimum distortion is $D_{\min}$, the main spirit of the IEENNS algorithm can be stated as follows:

If $(S_{\mathbf{x}} - S_{C_j})^2 \geq kD_{\min}$ **then** $D(\mathbf{x}, C_j) \geq D_{\min}$ and C_j will not be the nearest neighbor to $\mathbf{x}$

ElseIf $(V_{\mathbf{x}} - V_{C_j})^2 \geq D_{\min}$ **then** $D(\mathbf{x}, C_j) \geq D_{\min}$ and C_j will be rejected

ElseIf $(S_{\mathbf{x}} - S_{C_j})^2 + k(V_{\mathbf{x}} - V_{C_j})^2 \geq kD_{\min}$ **then** $D(\mathbf{x}, C_j) \geq D_{\min}$ and C_j will be rejected

Tchebichef moments of an N×N image block, $f(x, y)$ are given by [9]:

$$T_{pq}(f) = \frac{1}{\rho(p,N)\rho(q,N)} \sum_{x=0}^{N-1}\sum_{y=0}^{N-1} t_p(x)t_q(y)f(x,y) \quad p,q = 1,2,...N-1 \; ,$$

where $\quad t_n(x) = n!\sum_{k=0}^{n}(-1)^{n-k}\binom{N-1-k}{n-k}\binom{n+k}{n}\binom{x}{k}$.

These discrete moments are orthogonal and by scaling the polynom $t_n(x)$ we can obtain a set of orthonormal moments. Thus, we can write:

$$D_T(f,g) = \sum_{p\in P}\sum_{q\in Q}(T_{pq}(f(x,y)) - T_{pq}(g(x,y)))^2 \leq$$
$$\leq \sum_{x=0}^{N-1}\sum_{y=0}^{N-1}(f(x,y) - g(x,y))^2 = D(f,g), \quad P,Q \subset \{0,1\}$$

where $D(f,g)$ is defined as squared Euclidian distance between image f and image g .

Having the codebook $C = \{C_1, C_2, ..., C_N\}$, the input image block f and assuming that the current minimum distortion is $D_{\min} = D(f,C_q)$, the main idea of the algorithm can be stated as follows:

If $D_T(f,C_i) \geq D_{\min}$ **then** $D(f,C_i) \geq D_{\min}$. This means that C_i **will not** be the nearest neighbor to f and C_i will be rejected.

The complexity reduction is caused to reduction in number of addition and multiplications needed to compute $D_T(f,C_i)$ instead of computing $D(f,C_i)$. By choosing a cleaver searching sequence, experimental results shows that this proposed algorithm is faster than IEENNS algorithm, in terms of computational complexity.

RESULTS AND DISCUSSION

The images are 512×512 monochrome with 256 gray levels. An image is partitioned in 4×4 image blocks and the codebook is design using the Linde-Buzo-Gray (LBG) algorithm with Lena image as a training set. The Peppers and Baboon images are used as the test images. The proposed algorithm is compared to the Full Search, ENNS, IENNS, EENNS and IEENNS algorithms. Table 1 show the average number of operations per pixel for a codebook size of 512 codevectors.

Table 1: Comparison of average Number of Operations per Pixel

Codebook size	Method	Encoded image					
		Peppers			**Baboon**		
		Mult.	Add.	Comp.	Mult.	Add.	Comp.
512	Full Search	512	992	31.94	512	992	31.94
	IEENNS	27.43	42.85	46.56	74.25	119.06	128.31
	Proposed	**23.81**	**37.87**	**40.51**	**66.38**	**107.40**	**115.98**

CONCLUSIONS

In this paper new inequalities using Tchebichef moments are introduced. The proposed algorithm uses this inequalities to eliminate many of the impossible matching codewords wich cannot be eliminated by another algorithms. Experimental results confirm that the proposed algorithm is superior to the IEENNS algorithm.

REFERENCES

[1] Y. Linde, A. Buzo, and R. M. Gray, "An algorithm for vector quantizer design", *IEEE Trans. Commun*., vol COM-28, no. 1, pp.84-95, 1980

[2] A. Gersho and R. M. Gray, Vector quantization and signal compression, *Kluwer Academic Press*, Massachusetts, 1990

[3] N. Moayeri, D. L. Neuhoff, and W. E. Stark, "Fine-coarse vectorquantization," *IEEE Trans. Signal Processing,* vol. 39, pp. 1503–1515, July 1991.

[4] V. Ramasubramanian and K. K. Paliwal, "Fast k-dimensional tree algorithms for nearest neighbor search with application to vector quantization encoding," *IEEE Trans. Signal Processing,* vol. 40, pp. 518–531, Mar. 1992

[5] C. D. Bei and R. M. Gray, "An improvement of the minimum distortion encoding algorithms for vector quantization and pattern matching," *IEEE Trans. Commun.,* vol. COMM-33, pp. 1132–1133, Oct. 1985.

[6] S. W. Ra and J. K. Kim, "A Fast Mean-Distance-Ordered Partial Codebook Search Algorithm for Image Vector Quantization," *IEEE Trans. Circuits Syst. II*, vol. 40, no. 9, pp. 576–579, 1993

[7] C. H. Lee and L. H. Chen, "Fast closest codeword search algorithm for vector quantization," *Proc. Inst. Elect. Eng.*, vol. 141, no. 3, pp. 143–148, 1994.

[8] J.-S. Pan, Z.-M. L. Lu, and S.-H. Sun, "An Efficient Encoding Algorithm for Vector Quantization Based on Subvector Technique", *IEEE Trans. Image Processing*, vol. 12, no. 3, March 2003

[9] R. Mukundan, S.H. Ong, P.A. Lee, "Image Analysis by Tchebichef Moments", *IEEE Transaction on Image Processing*, vol. 10, No. 9, pp.1357-1364, September 2001