

Adaptive Image Transform Coding: A Fuzzy Approach for Classification and Bit Allocation

Wen-Yuan Liao¹ Tsang-Long Pao²

¹Lecture, Department of Computer Science and Engineering De-Lin Institute of Technology

²Associate Professor, Department of Computer Science and Engineering Tatung University

Abstract

An adaptive transform coding of images incorporated with fuzzy system is presented in this paper. First the concept of adaptive transform coding is introduced, then the principle use the fuzzy theory for classification and bit allocation is explained. This method is use of the 1-diemensional vector quantization to allocation the bit length for coding each pixel value. Fuzzy subimage classification is used to classify the subimage to be coded. Then, the bit allocation scheme uses different bit maps for classification. The proposed method has a good performance in objective and subjective sense in our simulation results.

Key word: adaptive transform coding, fuzzy theory, bit allocation, vector quantization.

以模糊理論作為分類與位元長度基礎之 可調式影像轉換編碼

廖文淵¹ 包蒼龍²

¹德霖技術學院資訊工程系專任講師

²大同大學資訊工程研究所副教授

摘 要

在本論文中我們提出一個以模糊理論作為編碼分類與位元長度配置依據之可調式數位影像轉換編碼技術。首先對可調式數位影像轉換編碼作一介紹，接著說明有關模糊理論的原理，及其應用在決定影像編碼位元長度與分類上的方法。此方法可視為一維向量量化的延伸，其將每一像素值以特定位元長度編碼，仍不影響影像品質，卻可以大大提高位元傳輸率(Bit Rate)，在現今多媒體網路上，對於高壓縮比有很大的需求，因此提出一個合理可用的技術。最後，實驗結果顯示本論文所提出的方法可以獲得不錯的效能。

I. Introduction

Image data coding has become very important in application such as communication, multimedia systems, robotics and other fields. Transmission of digital image data increases communication accuracy but requires increased bandwidth. Limited channel capacity favors image-compression techniques. These methods attempt to minimize the number of bits needed for coding an image and reconstruct it with little visible distortion.

Image coding often takes the form of transform coding. In transform coding, a transformation, perhaps an energy-preserving transform such as the discrete cosine transform, converts an image to uncorrelated data. We keep the transform coefficients with high energy and discard the coefficients with low energy, and thus compress the image data. Many methods for transform coding of images have proposed, even more the JPEG (Joint Photographic Experts Group) and MPEG (Moving Pictures Experts Group) standards use this concept. We shall apply the fuzzy methodology to a simple form of transform coding.

This approach proposes an adaptive image coding using discrete cosine transform coding and a fuzzy subimage classification for selection of the transform coefficients that will be coded. This bit allocation scheme is based on a subimage classification constructed using a bit map.

II. Adaptive Image Transform Coding

Adaptive cosine transform coding system classifies subimages into four classes according to their AC energy level and encode each class with different bit maps, The system assigns more bits to a subimage if the subimage contains much detail (large AC energy), and less bits if it contains less detail (small AC energy). DC energy refers to the constant background intensity in an image and behaves as an average. AC energy measures intensity variation about the background DC average. So the AC energy behaves as a sample-variance statistic.

The basic adaptive coding system identified in Fig.1 is constituted by several blocks. The image is first segmented in small subimages of 16×16 pixels. As widely known, the image energy within the transform domain is clustered around the lowest spatial frequencies. To make use of the characteristic of the image transform, the bit rate control is used to select the bit assignment for each bit in a subimage. The coefficients allocated for bits are then quantized, transmitted and stored.

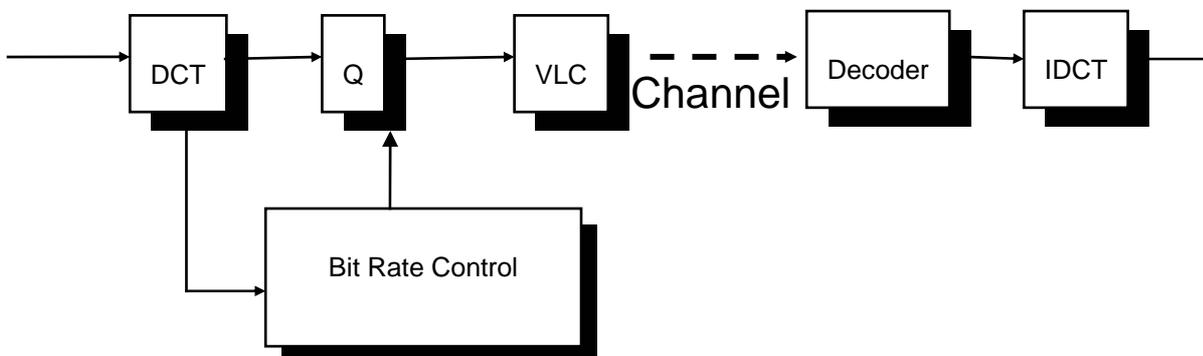


Figure 1: Block diagram of adaptive image transform coding.

The two-dimensional discrete cosine transform (DCT) pair of $N \times N$ image data $x(m, n)$ can be defined as

$$X(u, v) = \frac{4w(u)w(v)}{N^2} \sum_{n=0}^{N-1} \sum_{m=0}^{N-1} x(m, n) \cos \frac{(2m+1)u\pi}{2N} \cos \frac{(2n+1)v\pi}{2N} \quad (1)$$

$$x(m, n) = \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} w(u)w(v)X(u, v) \cos \frac{(2m+1)u\pi}{2N} \cos \frac{(2n+1)v\pi}{2N}$$

where $w(0) = \frac{1}{\sqrt{2}}$, and $w(k) = 1$ for $k = 1, \dots, N-1$. The DCT provides fast implementation, real-valued transform coefficients, and small boundary effects. Then divides an original image into 16×16 subimages and transforms each subimage with the 2-D DCT.

The adaptive transform coding system sorts subimages according to their AC energy and divides them into the 4 classes named 1, 2, 3 and 4. Class 1 contains the highest-activity subimages; class 4 contains the lowest-activity subimages. The AC energy within each subimage measures the activity level of that subimage.

The DC and AC energy (DCE and ACE) of a subimage are defined as

$$DCE = X^2(0,0), \quad (2)$$

$$ACE = \sum_u \sum_v X^2(u, v) - X^2(0,0) \quad , \quad (3)$$

where $X(u, v)$ denotes the 2-dimensional DCT coefficients of an image $x(m, n)$. $X(0, 0)$ denotes the background intensity level, the DC term. The other $X(u, v)$ terms contribute to the AC energy as part of an unnormalized sample variance.

This system uses the variance of each image element to compute 4 bit maps for each subimage class. Assign more bits for pixels with large variance, less bits for pixels with small variance.

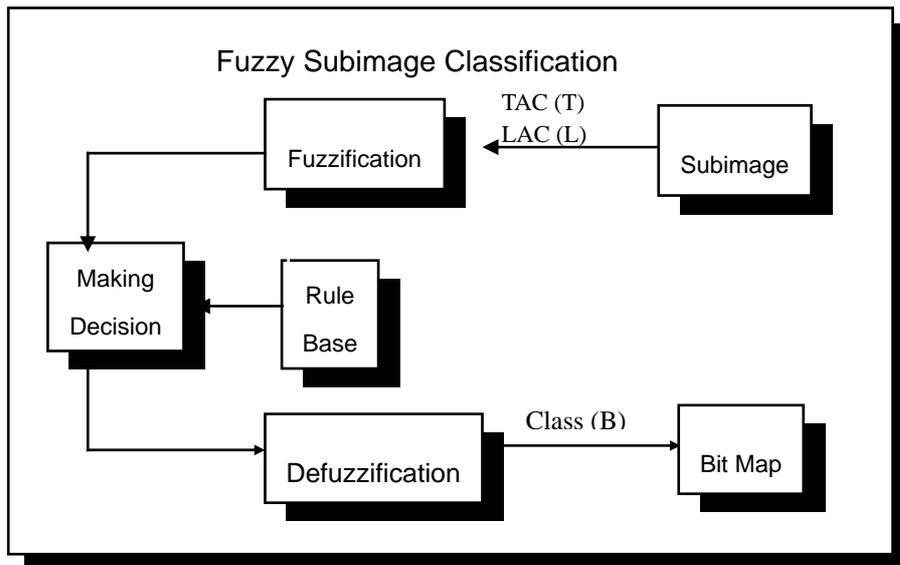


Figure 2: Block diagram of fuzzy subimage classification system.

III. Fuzzy Image Transform Coding

The proposed fuzzy image transform coding system is shown in Fig. 2. In general, a fuzzy control system is composed of several blocks, including fuzzification, defuzzification, rule base generator, and making decision. We will describe the detail design process in the following sections.

A. Fuzzification

The four fuzzy set BG (big), MD (medium), SL (small), and VS (very small) quantize the total AC energy T of a subimage. So the fuzzy variable T assumed only the four fuzzy-set labels BG, MD, SL, and VS, as shown in Fig. 3. To help make fuzzy decisions, we introduce the fuzzy variable L as the low-frequency AC energy. The L assumed only the two fuzzy-set labels SM (small) and LG (large).

The total AC energy T and the low-frequency AC energy L of a subimage in terms of the DCT coefficients $X(u, v)$ are defined as

$$T = \sum_{u=0}^{m-1} \sum_{v=0}^{m-1} X^2(u, v) - X^2(0,0) \quad , \quad (4)$$

$$L = \sum_{u=0}^{m/2-1} \sum_{v=0}^{m/2-1} X^2(u, v) - X^2(0,0)$$

where m equals the number of pixel rows or pixel columns in the $m \times m$ subimage, here $m = 16$.

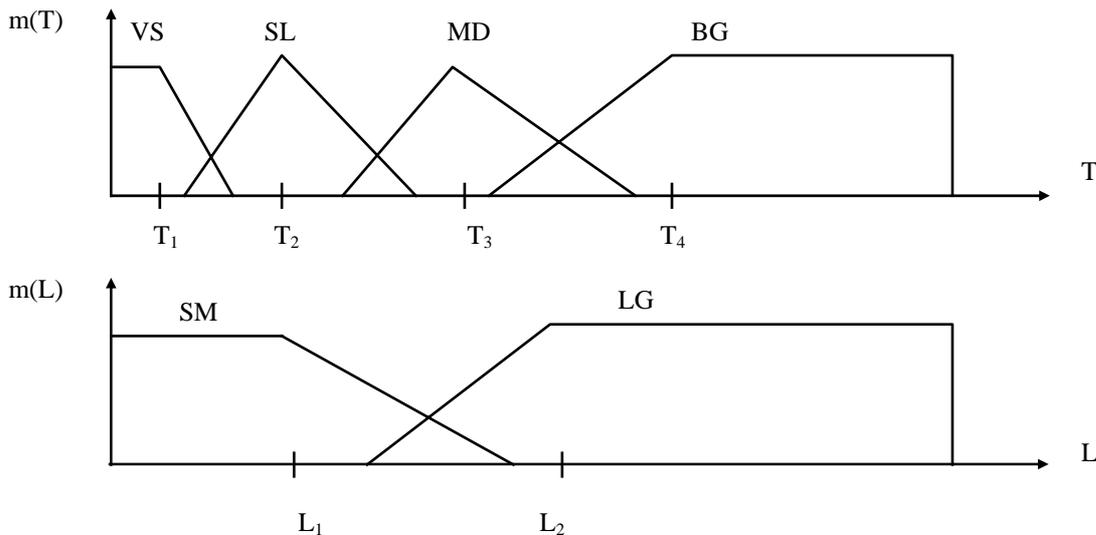


Figure 3: Fuzzy-set labels T and L.

B. Selection of Fuzzy-set values

We define the T_i and L_i to be the fuzzy-set values for the total AC energy and low-frequency AC energy respectively. We use percentage-scaled values of T_i and L_i scaled by the maximum possible total AC energy value. We compute the maximum total AC energy T_{\max} from the DCT coefficients of the subimage. In our simulation, $T_{\max} = 7,624.8$

The arithmetic average AC energy T_i and L_i for each class $i = 1, \dots, 4$ is defined as

$$\begin{aligned} T_i &= \frac{1}{64} \sum_{j=1}^{64} T_i^j \\ L_i &= \frac{1}{128} \sum_{j=1}^{128} L_i^j \end{aligned} \quad (5)$$

In our simulation of the Lenna image, $T_1 = 5.29$, $T_2 = 16.28$, $T_3 = 34.08$, and $T_4 = 60.44$; $L_1 = 8.76$, and $L_2 = 34.23$. Triangular fuzzy membership functions describe BG, MD, SL, and VS for fuzzy variable T peaked at the values T_1 , T_2 , T_3 , and T_4 respectively; the fuzzy set LG and SM for fuzzy variable L peaked at L_1 and L_2 respectively.

We classify subimages into four fuzzy classes B represented by the four fuzzy set labels HI (high), MH (medium high), ML (medium low), and LO (low). We encode the HI subimage with more bits and the LO subimage with less bits. The output fuzzy-set variable B is classified into four classes, as shown in Fig. 4.

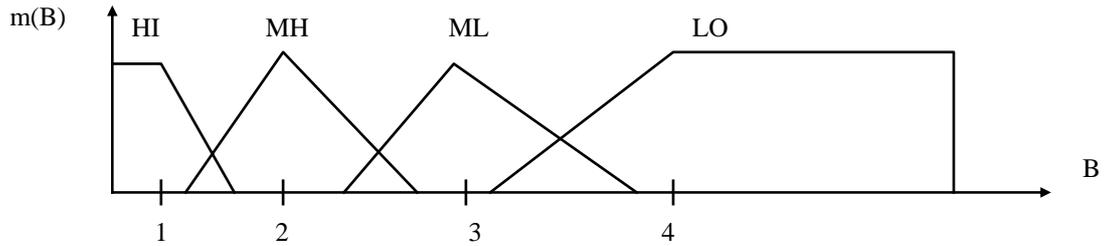


Figure 4: Fuzzy-set label B.

C. Reasoning Rules

The fuzzy rules base is presented in Table 1. For example, rule1 represents the association:

IF T is BG and L is LG, then class B corresponding to HI

L T	BG	MD	SL	LO
LG	HI	HI	ML	LO
SM	HI	MH	ML	LO

Table 1: Fuzzy rule bank for subimage classification.

D. Defuzzification

In our project, the method of defuzzification for the system uses the COA (center of area) method. The COA defines the defuzzification values of a fuzzy set as its fuzzy centroid. The calculation of the COA defuzzification can be simplified as:

$$y = \frac{\sum_{j=1}^n F(x_j)x_j}{\sum_{j=1}^n F(x_j)}. \quad (6)$$

IV. Simulation Results

The system encodes the Lenna image at approximately 1 bit/pixel. Fig. 5 shows the original Lenna and the compressed 8-to-1 compression. Fig. 6 shows the subimage classification map of the Lenna image. We use the four bit maps shown in Fig. 7 for at 1 bit/pixel compression.

We simulate the fuzzy transform coding system using the MATLAB, the simulation result is shown below.



Figure 5: The original and compressed Lenna image. (a) Original Lenna; (b) fuzzy encoding (8:1).

4	3	4	4	4	4	4	4	4	4	3	4	2	1	4	1
3	3	4	4	4	3	2	2	1	4	4	4	4	1	1	4
2	3	4	4	3	4	4	2	1	1	3	2	4	1	2	1
4	3	4	1	1	4	2	2	4	1	1	1	1	1	1	2
4	3	4	1	2	2	2	3	3	3	1	1	1	1	1	4
4	3	4	1	2	3	2	1	1	1	4	1	1	1	4	4
4	4	4	1	1	2	1	1	1	3	1	1	1	1	4	4
4	3	4	1	2	3	2	1	1	1	4	1	2	3	4	4
3	3	2	1	1	1	1	1	1	1	1	1	1	4	4	2
3	3	1	1	1	1	1	4	3	2	2	1	1	4	2	4
3	4	1	1	1	1	1	4	2	1	1	1	2	4	3	4
3	3	1	1	1	2	3	2	3	1	2	1	4	4	2	2
1	2	1	1	1	1	4	2	3	1	1	1	3	2	1	1
1	3	1	1	1	1	2	2	4	4	4	1	4	1	1	4
1	3	1	3	1	1	2	2	4	4	4	1	2	1	1	3
1	2	2	1	1	1	2	4	4	4	4	1	3	1	2	2

Figure 6: Subimage classification map of the Lenna image in Fig. 5. 1 indicates the highest-activity subimages; 4 indicates the lowest-activity subimages.

V. Conclusions

The adaptive transform coding process involves fuzzy classification. The result shows that the system requires few bits per pixel but maintains comparable compressed-image quality. By tuning the fuzzy rules, we can improve the performance of the compressed images. The coder presented is an efficient method for applications where the visual quality is more important than the number of bit the coded images.

8	7	6	5	4	3	3	2	2	1	1	1	0	0	0	0
7	6	6	5	4	3	3	2	2	1	1	1	0	0	0	0
6	5	5	4	4	3	3	2	2	1	1	1	0	0	0	0
5	5	4	4	4	3	3	3	2	2	1	1	1	0	0	0
4	4	4	3	3	3	3	2	2	2	1	1	1	0	0	0
3	3	3	3	3	2	2	2	2	2	1	1	1	1	0	0
3	3	3	3	3	2	2	2	2	1	1	1	1	1	0	0
2	2	2	3	2	2	2	1	1	1	1	1	1	1	0	0
2	2	2	2	3	2	2	1	1	1	1	1	1	1	0	0
2	2	2	2	2	2	1	1	1	1	1	1	1	1	0	0
1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0
1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0
1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0

Class 1

8	6	5	4	4	3	2	2	2	1	1	1	0	0	0	0
6	5	5	4	4	3	2	2	2	1	1	1	0	0	0	0
5	5	4	4	4	3	3	2	2	1	1	1	0	0	0	0
4	4	4	3	3	3	3	2	2	2	1	1	0	0	0	0
3	3	3	3	3	3	3	2	2	2	1	1	1	0	0	0
3	3	3	3	2	2	2	2	2	2	1	1	1	1	0	0
2	2	2	2	2	2	2	2	2	2	1	1	1	1	0	0
2	2	2	3	3	2	1	1	1	1	1	1	1	1	0	0
2	2	2	3	4	3	2	1	1	1	1	1	0	0	0	0
1	2	1	2	3	2	1	1	1	1	1	0	1	0	0	0
1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0
1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0
1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0
1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0
1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0

Class 2

8	5	4	3	3	2	2	1	1	1	1	0	0	0	0	0
5	5	4	4	3	3	2	2	1	1	0	0	0	0	0	0
4	4	3	3	3	3	2	2	1	1	1	0	0	0	0	0
3	3	3	3	3	2	2	2	1	1	1	0	0	0	0	0
3	3	3	2	2	2	2	1	1	1	1	0	0	0	0	0
2	2	2	2	2	2	1	1	1	1	1	0	0	0	0	0
2	2	2	2	2	1	1	1	1	1	1	0	0	0	0	0
2	1	1	1	2	1	1	1	1	0	0	0	0	0	0	0
1	1	1	2	2	2	1	1	1	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
1	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0
1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0

Class 3

8	3	3	2	1	1	0	0	0	0	0	0	0	0	0	0
3	3	2	2	1	1	1	1	0	0	0	0	0	0	0	0
2	2	2	1	1	1	1	1	0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Class 4

Figure 7: Example of bit maps at approximately 1 bit/pixel.

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