Engineering Science and Technology, an International Journal 19 (2016) 769–781

HOSTED BY

Contents lists available at ScienceDirect

Engineering Science and Technology, an International Journal

journal homepage: http://www.elsevier.com/locate/jestch

Full Length Article

Fast vector quantization using a Bat algorithm for image compression

Chiranjeevi Karri *, Umaranjan Jena

Department of Electronics and Telecommunication Engineering, Veer Surendra Sai University of Technology (VSSUT), Burla 768018, Odisha, India

ARTICLE INFO

Article history:
Received 29 July 2015
Received in revised form
6 November 2015
Accepted 6 November 2015
Available online 17 December 2015

Keywords:
Vector quantization
Linde–Buzo–Gray (LBG)
Particle swarm optimization (PSO)
Quantum particle swarm algorithm (QPSO)
Honey bee mating optimization (HBMO)
Firefly algorithm (FA)
Bat algorithm (BA)

ABSTRACT

Linde–Buzo–Gray (LBG), a traditional method of vector quantization (VQ) generates a local optimal codebook which results in lower PSNR value. The performance of vector quantization (VQ) depends on the appropriate codebook, so researchers proposed optimization techniques for global codebook generation. Particle swarm optimization (PSO) and Firefly algorithm (FA) generate an efficient codebook, but undergoes instability in convergence when particle velocity is high and non-availability of brighter fireflies in the search space respectively. In this paper, we propose a new algorithm called BA-LBG which uses Bat Algorithm on initial solution of LBG. It produces an efficient codebook with less computational time and results very good PSNR due to its automatic zooming feature using adjustable pulse emission rate and loudness of bats. From the results, we observed that BA-LBG has high PSNR compared to LBG, PSO-LBG, Quantum PSO-LBG, HBMO-LBG and FA-LBG, and its average convergence speed is 1.841 times faster than HBMO-LBG and FA-LBG but no significance difference with PSO.

1. Introduction

Image compression plays a major role in applications like internet browsing, medical science, navy applications, TV broadcasting and many more applications. Several techniques have been proposed by many researchers over the past decades for image compression. Vector Quantization (VQ) technique, performance is better than scalar quantization methods such as pulse code modulation (PCM), differential PCM (DPCM), Adaptive DPCM. Vector Quantization (VQ) [1,2] is basically a c-means clustering method widely used for image compression, pattern recognition [3,4], speech recognition [5], face detection [6] speech and image coding because of its excellent rate distortion performance. VQ is popular because it has simple decoding structure and can provide high compression ratio. Basically VQ is performed in three steps: 1. Vector formation: – division of image into non-overlapping blocks or vectors called input vectors, 2. Codebook generation: – a set of representative image blocks of the input blocks (vectors) is selected which is called a codebook and each representative image vector is called a codeword 3. Quantization: – here each input vector is approximated to a codeword in the codebook and corresponding index of this codeword is transmitted. VQ methods are classified into two categories, namely crisp and fuzzy [7]. Crisp VQ is based on hard decision making processes and appears to be sensitive in codebook initialization. The most representative algorithms of this category are the c-means. To improve the behavior of c-means, Linde et al. introduced the Linde–Buzo–Gray (LBG) algorithm, which begins with the smallest codebook size and gradually increase it using a splitting procedure [8]. The performance of the LBG is improved by embedding special functions called utility measures in the learning process. Fuzzy VQ is carried out in terms of fuzzy cluster analysis. The most representative algorithms of this category is the fuzzy c-means. The fuzzy c-means assume that each training vector belongs to multiple clusters with different participation degrees (i.e. Membership degrees). Therefore, the learning is a soft decision making process [9]. LBG Algorithm undergoes local optimum problem [10]. So Patane and Russo proposed a clustering algorithm called enhanced LBG (ELBG) [11]. They used the concept of utility of a codeword to overcome the local optimal problem of LBG by shifting the lower utility codewords to the one with higher utility. Recently, the evolutionary optimization algorithms had been developed to design the codebook for improving the results of LGB algorithm. Rajpoot, Hussain, Saleem and Qureshi designed a codebook by using an ant colony system (ACS) algorithm [12]. In this algorithm, codebook is optimized by representing the vector coefficients in a bidirectional graph, followed by defining a suitable mechanism of depositing pheromone on the edges of the graph. Tsaia, Tsengb, Yangc, and Chiangb proposed a fast ant colony optimization for codebook generation by observing the redundant calculations [13]. In addition, particle swarm optimization (PSO) vector quantization [14] outperforms LBG algorithm which is based on updating the global best (gbest) and local best (lbest) solution. Feng, Chen, and Fun showed that Evolutionary fuzzy particle swarm optimization algorithm [15] has better global and robust performances than LBG learning

* *Corresponding author.* Tel.: +91 9441177331, fax: (0663)2430204.
E-mail address: chiru404@gmail.com (C. Karri).
Peer review under responsibility of Karabuk University.

http://dx.doi.org/10.1016/j.jestch.2015.11.003
2215-0986/

algorithms. Quantum particle swarm algorithm (QPSO) was proposed by Wang, Feng, Huang, Zhou, and Liang to solve the 0–1 knapsack problem [16]. The QPSO performance is better than PSO as it computes the local point from the *pbest* and *gbest* for each particle and updates the position of the particle by choosing appropriate parameters u and z.

Horng and Jiang applied honey bee mating optimization algorithm for Vector quantization [17]. HBMO has high quality reconstructed image and better codebook with small distortion compared to PSO-LBG, QPSO-LBG and LBG algorithm. Horng applied a firefly algorithm (FA) to design a codebook for vector quantization [18]. The firefly algorithm has become an increasingly important tool of Swarm Intelligence that has been applied in almost all areas of optimization, as well as engineering problems. Firefly algorithm is encouraged by social activities of fireflies and the occurrence of bioluminescent communication. A Firefly with lighter intensity value move towards the brighter intensity firefly, and if there is no brighter firefly then it moves randomly. Chang, Chiang, Yeh proposed a tree structured vector quantization for fast codebook design with the help of employing the triangle inequality to achieve efficient pruning of impossible codewords [19]. Chen, Hwang and Tsou proposed a fast codebook search algorithm based on triangular inequality estimation [20]. Kekre, Sarode, Sange, Natu and Natu proposed a fast codebook search algorithm with different codebook sizes in 8, 16, 32, 64, 128 and 256 based on the kekre's fast codebook generation algorithm [21]. Kekre, Sarode, Thepade and Vaishali proposed a Kekre's fast codebook generation in VQ with various color spaces for colorization of grayscale images [22]. Yang, RuiXia, Wang, and Jiao proposed an Evolutionary clustering based vector quantization for image compression based on One-step gradient descent genetic algorithm (OSGD-GA). OSGD-GA is designed for optimizing the codebooks of the low-frequency wavelet coefficient by defining the importance of each coefficient and utilizing fuzzy membership to address the automatic clustering [23]. Multivariate vector quantization (MVQ) approach is useful for compression of hyper spectral imagery (HSI) based on a linear combination of two codewords from the codebook, and the indexed maps and their corresponding coefficients are separately coded and compressed [24]. Contextual vector quantization (CVQ) compresses the medical ultrasound (US) images [25]. Contextual region is defined as a region containing the most important information and must be encoded without considerable quality loss. Attempts are made to encode this region with high priority and high resolution CVQ algorithm. Huanga, Wanga and Chen proposed a dynamic learning vector–scalar quantization for compression of ECG image by forming DWT coefficients into tree vector (TV) and on which vector–scalar quantization is performed [26]. Tripathy, Dash and Tripathy proposed a network layout optimization based on dynamic programming using optimization techniques [27]. Tsolakis et al. (in 2012) proposed a Fuzzy vector quantization for image compression based on competitive agglomeration and a novel codeword migration strategy [28]. George et al. proposed an improved batch fuzzy learning vector quantization for image compression [29]. Tsekouras (in 2005) proposed a fuzzy vector quantization by assigning an input vector to more than one codeword based on the crisp relation [30]. Tsolakis et al. developed a fast fuzzy vector quantization for gray scale image compression by combining three different learning modules. Those are: 1. Remove codewords that are affected by a specific training pattern; 2. Reduce the number of training patterns; 3. Codewords of small clusters have moved to the neighborhood of large ones [31].

Bat algorithm (BA) is a nature inspired Metaheuristic algorithm developed by Yang in 2010 [32]. There is functional similarity between bat algorithm and radio detection and ranging (RADAR). The radar works based on examination of reflected signals/echo signal from the object. Similarly, the basic idea behind Bat algorithm is an echolocation feature of micro bats. Bat algorithm is based on the echolocation behavior of micro bats with varying pulse rates of emission and loudness. The bat emits some sounds with different pulse rate and loudness. These sound signals are reflected back from objects called echo signals. With these echo signals, bats can determine the size of the object and distance to object, speed of the object and even their texture in fractions of a second because of their sophisticated sense of hearing. Frequency tuning, automatic zooming and parameter control features helps the Bat algorithm to be efficient and speedy. Also Bat algorithm is simple and flexible. A detailed comparison of bat algorithm with LBG, PSO, QPSO, HBMO and FA for image compression with vector quantization is given in Tables 5–12 and Figs. 6–15. From comparison, we conclude clearly that BA has advantages over other algorithms. Along with optimization problems [33], Bat algorithm can also be applied to classification, clustering, data mining [34], image matching [35], Fuzzy logic [36], and parameter estimation [37] problems.

This paper is organized into five sections including the introduction. In section 2, recent methods of codebook design are discussed along with their algorithms. The proposed method of BA-LBG algorithm is presented with the procedures in section 3. The results and discussions are given in section 4. Finally, the conclusion is given in section 5.

2. Recent methods of codebook design for VQ

As discussed in section 1, the major important technique for image compression is Vector Quantization (VQ), which is to be optimized. The Vector Quantization (VQ) is one of the block coding technique for image compression. Codebook design is an important task in the design of VQ that minimizes the distortion between reconstructed image and original image with less computational time. Fig. 1 shows the encoding and decoding process of vector quantization. The image (size $N \times N$), to be vector quantized, is subdivided into N_b $(\frac{N}{n} \times \frac{N}{n})$ blocks with size $n \times n$ pixels. These divided image blocks or training vectors of size n × n pixels are represented with X_i $(i = 1, 2, 3, \ldots, N_b)$. The Codebook has a set of code words, where C_i $(i = 1 \ldots NC)$ is the i^{th} codeword. The total number of codewords in Codebook is N_c. Each subdivided image vector is (approximated) represented by the index of a codeword based on the minimum Euclidean distance between the corresponding vector and code words. The encoded results from the index table. During the decoding procedure, the receiver uses the same codebook to translate the index back to its corresponding codeword for reconstructing the image. The distortion D between training vectors and the codebook is given as

$$D = \frac{1}{N_c} \sum_{j=1}^{N_c} \sum_{i=1}^{N_b} u_{ij} \cdot \|X_i - C_j\|^2 \tag{1}$$

Subject to the following constraints:

$$D = \sum_{j=1}^{N_c} u_{ij} = 1 \quad i \in \{1, 2, \ldots, N_b\} \tag{2}$$

u_{ij} is one if X_i is in the j^{th} cluster, otherwise zero.

Two necessary conditions exist for an optimal vector quantizer.

(1) The partition R_j, $j = 1, \ldots, N_c$ must satisfy

$$R_j \supset \{x \varepsilon X : d(\mathrm{c}, \mathrm{C}_j) < d(\mathrm{x}, \mathrm{C}_k), \quad \forall \mathrm{k} \neq \mathrm{j}\} \tag{3}$$

(2) The codeword C_j must be given by the centroid of R_j:

$$C_j = \frac{1}{N_j} \sum_{i=1}^{N_j} x_i \quad x_i \in R_j \tag{4}$$

where N_j is the total number of vectors belonging to R_j.