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Entropy-constrained reflected residual vector quantization: A realization of large block vector quantization

Muhammad A.U. Khan [a], Wail A. Mousa [b], Tariq M. Khan [c,*]

[a] Department of Electrical and Computer Engineering, Effat University, Jeddah, Saudi Arabia
[b] Electrical Engineering Department, King Fahd University of Petroleum & Minerals, Saudi Arabia
[c] Electrical Engineering Department, COMSATS Institute of Information & Technology, Islamabad, Pakistan

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ABSTRACT

Vector quantization (VQ) techniques have been used for a number of years for developing successful data compression and classification algorithms. Vector quantization is inherently an unsupervised data clustering technique that smartly adopts to the given data statistics and is thus used in large variety of tasks. The gains associated with a VQ system are largely linked to the size of the block used. However, the complexity increases exponentially with an increase in block length. In conventional methods, a dimensional reduction pre-processing step is invoked before the VQ system in order to reduce the block length. For some data sources this may be unacceptable approach such as with hyper-spectral data. Therefore, a large block VQ is needed to fully exploit the linear and non-linear correlation in a data source. We propose an entropy-constrained reflected residual VQ (EC-RRVQ) as one alternative for large block vector quantization. The reflected residual VQ, a type of multistage VQ, has constrained structure with multiple stages having small-size code-books. The use of multiple code-books and a reflection constraint makes the computational complexity linearly depend on the number of stages involved. The linear increase in complexity prompted us to pose EC-RRVQ as a contender in the list of options of large block vector quantization implementation algorithms. Experimental results indicate that good image reproduction quality can be accomplished at relatively low bit rates. The performance of a 64-stage 16×16 EC-RRVQ at 0.175 bits per pixel is 23.75 dB with 96 vector distortion calculations per source vector, while the number for previously proposed large-dimensional entropy-constrained residual VQ (EC-RVQ) designed under the same specifications is 21.17 dB with 1212 vector distortion calculations per source vector.

1. Introduction

Vector quantization (VQ) techniques have been used for a number of years for developing some of the most successful data compression schemes. Vector quantization is inherently an unsupervised data clustering technique that smartly adopts to the given data statistics and provides a partitioning of the data space according to data statistics and user-defined error criterion. Due to its simple implementation ease at modeling different data sources and, sensitivity in unsupervised cluster geometry with error criterion definition, VQ has been a method of choice for a number of applications other than data compression in recent years. In [1], authors employed vector quantization for classification of partial power discharge (PD) pattern characteristics. The results show that while the implementation of such a classifier is simple, it achieves higher classification rates compared to a previously employed multi-layer perceptron artificial neural net (ANN) classifier. The improved performance is due to better generalization characteristics of VQ over the ANN. A wavelet-based vector quantization approach proposed in [2] provides improved lossless data compression of the electrocardiogram due to the ability of VQ to extract linear and non-linear dependencies among block elements. The work reported in [3] demonstrates increased effectiveness of VQ in image retrieval from a database, over a conventional expectation–maximization methodology. Vector quantization has also been extended to help in copyright protection, copy protection, and integrity verification, three important issues in the rapid growth of Internet technologies [4]. Vector quantization in conjunction with hidden Markov modeling (HMM) has become a powerful tool in pattern recognition. One instant where this combination is employed is reported in [5], where power quality disturbances are

* Corresponding author.
E-mail addresses: mohammad_a_khan@yahoo.com (M.A.U. Khan), wailmousa@kfupm.edu.sa (W.A. Mousa), tariq045@gmail.com (T.M. Khan).

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classified by assigning a chain of labels using vector quantization approach. Vector quantization, due to its ability to adopt to various source models, has also been implemented in a VLSI architecture for real-time scenarios [6] and can be made hardware friendly [7]. In [8] it has been used for determining man-made objects and changes in imagery. In [9], weighted vector quantization of discrete-cosine transform coefficient is performed for speech coding.

The vast scope of applications has sparked renewed interest in the design of VQ algorithms. To suit this ever-increasing application pool, many different types of training set based practical algorithms for VQ surfaced, such as classified VQ [10], address VQ [11,12], finite-state VQ [13], side match VQ [14], mean-removed classified VQ [15], and predictive address VQ [12]. Set the stage for our VQ work, let us focus on a simple unconstrained VQ. The operation of VQ includes dividing the data elements to be compressed into a group of samples (vectors) and each vector is compared with code words of a code-book to find the best reproduction vector. In the encoding process, an index, which points to the closest code word, is determined and sent over the channel. In the decoding process, the received index is used to access a corresponding code word from an identical code-book.

Though theoretical justification has been provided quite a long-time ago by the Shannon block coding theorem for employing block of samples over individual samples [16], the implementation of such a VQ still needs to be investigated. The gains associated with vector quantizer are also formally organized and enumerated in a relatively recent work [17]. The authors decompose the vector quantizer advantage in three independent factors. The factors are referred to as space-filling advantage, the shape advantage, and the memory advantage. Out of these three advantages, the memory advantage that relates to exploiting the linear and non-linear dependencies among the data samples of a given block is highly desired in compression scenarios. The authors make it clear that all these three gains depend heavily on the length of the block or vector dimension employed. The larger the length of the block, the higher will be the performance gains of a given VQ system. For instance, the memory gain increases from 5.05 dB for a two-dimensional VQ to 10.01 dB for a 100-dimensional VQ for a first-order Gauss–Markov data source. Given this proven superiority of a large-block VQ, one is naturally inclined to go for higher dimensions for a given VQ application. However, there is a price tag attached to higher-dimensional VQ in terms of computation and memory burden. For example to develop a 100-dimensional VQ with rate 1 bit/sample, this would require designing and searching code-book of size 2100, which would practically impossible.

Till recently, keeping in view the complexity barrier, the normal practice has been to use small blocks like 16-dimensional or at the high-end 64-dimensional VQs. The small-dimensional VQs reduce the VQ memory advantage but are less computationally complex. The reduction in VQ memory advantage can be partially compensated by employing a pre-processing step in the form of linear prediction or transforms [18]. The actual success of such a joint operation – a linear transform follow-up with small block VQ – lies entirely on the assumption that the neighboring data samples are linearly correlated and have a small non-linear dependency support region. Whereas in real life situation, there are instances where data may possess linear as well as non-linear dependencies over large areas. For some data sources, it may not be unwise to think that non-linear correlations are stronger than linear correlation and that these correlations may have a much wider support among the neighboring data samples. One such data source is hyper-spectral imagery, which is inherently higher dimensional in nature. Hyper-spectral imagery is acquired from sensors with very high spatial, spectral, and radiometric sensitivity. Because the images have high spatial and spectral resolutions, together with numerous spectral bands, the associated data volumes are enormous, which has recently become an urgent challenge to data storage and transmission. Although partial success has been achieved by using predictive-based VQ techniques [19,20], transform-based VQ methods [21] or gain-shape VQ [22], there is a desire to deploy VQ for large three-dimensional cubes of pixels that consists of large two-dimensional spatial region and which goes across many spectral bands. The other instances include the compression of three-dimensional ultra-spectral sounder data, which are used in improved weather and climate prediction and is a challenging task given its unprecedented size. In [23], a fast vector quantization scheme with optimal bit allocation is proposed for lossless compression of sounder data, however the proposed block size is small. Many practical multi-sensors tracking systems are based on some form of track fusion, in which local track estimates and their associated co-variances are shared among sensors. Co-variance matrices employed are usually vector quantized. It is seen that little fused accuracy is lost using VQ with its appealing reduction in bandwidth [24]. The covariance matrices should be large in size to take into account the large time-series past history of various sensors involved. The compression and classification scenarios discussed here are in need of truly large-dimensional VQ system.

Desires employing large-dimensional VQ without having a pre-processing step have prompted researchers to think about employing constrained code-book structures within a VQ paradigm. This means that the code words cannot have arbitrary locations as points in k-dimensional space but are distributed in a restricted manner that allows a much simpler search for finding the best reproduction vector. Any constraints imposed on the code-book as part of the design process can generally be expected to lead to an inferior code-book for a given rate and dimension. However, if the large block advantage is significantly high enough, such an impairment is minimal. Isolated examples of this idea have appeared in the literature. Trellis source codes can be associated with the category of constrained large-dimensional vector quantization. The labeling of the trellis branches has been improved in a recent research work [25]. In the field of neural networks, self-organizing maps (SOMs) can be employed to realize structural large-dimensional VQs [26]. Lattice vector quantization can effectively be built for large-dimensional VQs [27]. In [28], a companded union of translated Z-lattices has been employed to form low complexity large-dimensional VQs. One popular example, examined in this work, is the use of multiple small size code-books while keeping the input vector dimension large. Such a VQ with constrained code-book structure is referred to as residual VQ.

Residual VQ is a structurally constrained variant of VQ that simultaneously reduces both the computation and memory normally associated with a VQ. Residual VQ consists of a sequence of VQ stages, where each stage encodes the residual (error) vector of the prior stage. Later on, to improve the compression capabilities of an RVQ system, entropy coding was combined with multiple code-book structure [29]. In entropy-constrained RVQ (EC-RVQ), the individual stage indices are entropy coded based on their respective probabilistic models. More recently, an alternative EC-RVQ design algorithm was introduced in [30], where the inherent dependencies of memory sources are exploited by employing a high-order conditional entropy-coder. The design is known as the conditional entropy-constrained RVQ (CEC-RVQ). The high-order CEC-RVQ can achieve a 30–40% reduction in bit rate over EC-RVQ while maintaining the same reconstruction quality. However, the focus of CEC-RVQ is for small dimensions like 4 or 16. For moderately large dimensions like 64 dimensions, the performance of CEC-RVQ for natural image encoding is almost similar to conventional EC-RVQ. Given this observation and our interest in achieving large vector dimensionality with EC-RRVQ, we use EC-RVQ as the standard of coding comparisons with large-block EC-RRVQ. Furthermore, the research of this paper provides an extended investigation of the preliminary