IMPROVING SINGLE-PASS ADAPTIVE VQ

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ABSTRACT

Constantinescu and Storer in [2] introduced a single-pass vector quantization algorithm that with no specific training or prior knowledge of the data was able to achieve better compression results with respect to the JPEG standard, along with a number of computational advances such as: adjustable fidelity / compression tradeoff, precise guarantees on any $l \times l$ sub-block of the image, fast table-lookup decoding. In this paper we improve that basic algorithm by blending it with the mean shape-gain vector quantization (MSGVQ) compression scheme. This blending allows a slightly better performance in terms of compression and a clear improvement in visual quality.

1. INTRODUCTION

Vector quantization ([1]) is a process of approximating sampled analog data, such as speech or images, by replacing block (*vectors*) of input data by similar vectors from a dictionary of vectors (*codebook*). One significant drawback of vector quantization is that for a given rate, the optimal VQ codebook requires computational and memory resources exponentially growing with the block length. A product code framework is usually used to simplify the quantization by mapping the input signal into a smaller domain.

In [2, 3] an adaptive vector quantization algorithm has been introduced that combines the ability of lossless adaptive dictionary methods to process data in a single pass with the ability of vector quantization to accurately approximate data. The algorithm typically equals or exceeds the JPEG standard and it often out-performs traditional trained VQ. At each step the algorithm select a point of the input image p (also called growing point). The encoder uses a match heuristic to decide which block b of a local dictionary D(that stores a constantly changing set of vectors) is the best match for the sub-block anchored in p of the same shape as b. For a given threshold T, the match heuristic chooses the largest block for which the distance from the original block (typically the mean square error) is less or equal to a fixed B. Carpentieri

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threshold *T*. The basic structure of the encoding algorithm is the following:

- 1. Initialize the *local dictionary D* to have one entry for each pixel of the input alphabet and the initial set of *growing points (GPP)*.
- 2. Repeat until GPP is empty:
 - (a) Use a *growing heuristic GH* to choose a growing point *GP* from *GPP*.
 - (b) Use a *match heuristic MH* to find a block b in D that matches with acceptable fidelity the subblock anchored in GP.
 Transmit [log|D|] bits for the index of b.
 - (c) Use a *dictionary update heuristic DUH* to update D (if D is full, first use a *deletion heuristic DH* to make space).
 Update GPP according to a *growing points update heuristic GPUH*.



Figure 1: On-Line Adaptive Vector Quantization

2. MEAN SHAPE-GAIN BASED BLOCK MATCHING

One significant drawback of standard vector quantization is the computational and memory requirement which restrict its applicability. Many attempts have been made to ease this problem. One of them is to use product code techniques [1]. Mean shape gain vector quantization is part of this class of techniques and has been first introduced in [4]. Essentially it works as follows: for each $\bar{x} \in \mathbb{R}^n$, define

$$m = \frac{1}{n} \sum_{i=1}^{n} x_i$$

$$g = ||\overline{mr}|| = \sqrt{\overline{mr}t \cdot \overline{mr}}$$

$$ifg \neq 0, \overline{s} = \frac{1}{q}\overline{mr}$$

where $\overline{mr} \in \mathbb{R}^n$, $\overline{mr} = \overline{x} - m\overline{1}$, $\overline{1}$ is the vector of ones in \mathbb{R}^n . Then \overline{x} can be decomposed as

$$\bar{x} = g \cdot \bar{s} + m \cdot \bar{1}.$$

The encoding consists of approximating \bar{x} by the vector

$$\hat{x} = \hat{g} \cdot \hat{s} + \hat{m} \cdot \bar{1}$$

that minimizes the mean square error

$$d(\bar{x}, \hat{x}) = ||\bar{x} - \hat{x}||^2.$$

The approximation is made by quantizing separately the mean, the gain and the shape. The net result of this approach is that it is possible to greatly increase the size of the codebook with a small amount of extra storage.

3. IMPROVING AVQ

In this section we show how it is possible to apply the transformation of the input vectors similar to MSGVQ to the adaptive VQ proposed in [2, 3] to improve its performances. Namely we changed the *match heuristic* in Step 2.a of Figure 1 as follows: let m_b , g_b and \bar{s}_b be respectively the mean, the gain and the shape of the block b in the dictionary and m_{GP} , g_{GP} and \bar{s}_{GP} be respectively the mean, the gain and the shape of the block x anchored in GP of the same size and shape of b. Compute the approximating vector

$$\hat{x} = g_{GP} \cdot \bar{s}_b + m_{GP} \cdot \bar{1}$$

and chooses b as the current match if its size is maximum and the distance $d(x, \hat{x})$ is less or equal to the fixed threshold. Once the best match is found, it is necessary to transmit to the decoder m_{GP} and g_{GP} along with the index of b in the dictionary. In order to minimize the entropy of the output stream, the mean is differentially encoded and fed to an arithmetic coder. For g_{GP} there is no gain with the differential encoding, so it is just transmitted using a different model for the arithmetic coder.

4. EXPERIMENTAL RESULTS

We tested the revised version of AVQ on many gray-scale images and it turns out that there is an average increase on of the compression (up to 18%), but the most evident result is that, for a fixed signal-to-noise ratio (SNR), the visual quality of the image encoded using the mean shape-gain method is substantially better that the one obtained using the plain version of AVQ. The following table shows some compression results on four well known images:

	AVQ	MGS-AVQ
	(SNR / C. R.)	(SNR / C.R.)
WomanHat	26.99 / 12.608	27.01 / 13.919
	30.01 / 8.095	30.01 / 9.163
	35.01 / 4.166	35.02 / 4.471
LivingRoom	24.53 / 10.478	24.51 / 10.806
	27.00 / 7.391	27.00 / 7.772
	32.02 / 3.952	32.03 / 4.3
Peppers	24.98 / 14.390	24.99 / 15.802
	26.50/11.157	26.50 / 13.208
	30.10 / 6.020	30.10 / 6.305
HotelLotus	24.00 / 11.217	23.96 / 11.006
	27.20 / 7.331	27.20 / 7.867
	30.84 / 4.753	30.84 / 5.04

Table 1: AVQ versus MGS-AVQ

Figure 2, 3 and 4 compare AVQ and MGS-AVQ in terms of the visual quality obtained by coding WomanHat, LivingRoom and Peppers at a SNR around 27db, 24.5db and 26.5db respectively. More compression results and quality comparisons can be found at [6].

The *match heuristic* has to recompute the mean shapegain transformation for each comparison with the dictionary (we are using a dictionary with 4096 entries) and this sligtly slows down the algorithm. On the other hand our implementation still uses a full search in the dictionary to find the best match, while it is possible to reorganize D in a tree structure such that the *match heuristic* is applied only to a constant number of indices of the dictionary without having significant losses in compression and/or quality.

5. CONCLUSION

We have presented an improvement to the single-pass, lossy, compression algorithm presented in [2]. The key idea is to blend the AVQ algorithm with the mean shape-gain Vector quantization scheme.

Experimental results shows that the visual quality of the compressed data is clearly improved and the price is just a minimal slow down of the algorithm.



Figure 2: WomanHat

6. REFERENCES

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Figure 3: LivingRoom



Figure 4: Peppers