

IMPROVING SINGLE-PASS ADAPTIVE VQ

F. Rizzo, J. A. Storer

Computer Science Department
Brandeis University
Waltham, MA 02454-9110, USA
{frariz, storer}@cs.brandeis.edu

B. Carpentieri

Dipartimento di Informatica ed Applicazioni
Universita' di Salerno
84081 Baronissi (SA), Italy
bc@dia.unisa.it

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

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 sub-block anchored in GP .
Transmit $\lceil \log |D| \rceil$ 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* $GPUH$.

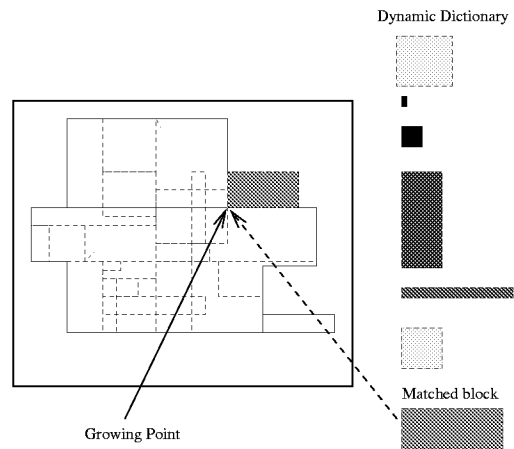


Figure 1: On-Line Adaptive Vector Quantization

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 $\bar{x} \in R^n$, define

$$\begin{aligned} m &= \frac{1}{n} \sum_{i=1}^n x_i \\ g &= \|\bar{m}\bar{r}\| = \sqrt{\bar{m}\bar{r}^t \cdot \bar{m}\bar{r}} \\ \text{if } g \neq 0, \bar{s} &= \frac{1}{g} \bar{m}\bar{r} \end{aligned}$$

where $\bar{m}\bar{r} \in R^n$, $\bar{m}\bar{r} = \bar{x} - m\bar{1}$, $\bar{1}$ is the vector of ones in R^n . Then \bar{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 than the one obtained using the plain version of AVQ. The following table shows some compression results on four well known images:

	AVQ (SNR / C. R.)	MGS-AVQ (SNR / C.R.)
WomanHat	26.99 / 12.608 30.01 / 8.095 35.01 / 4.166	27.01 / 13.919 30.01 / 9.163 35.02 / 4.471
LivingRoom	24.53 / 10.478 27.00 / 7.391 32.02 / 3.952	24.51 / 10.806 27.00 / 7.772 32.03 / 4.3
Peppers	24.98 / 14.390 26.50 / 11.157 30.10 / 6.020	24.99 / 15.802 26.50 / 13.208 30.10 / 6.305
HotelLotus	24.00 / 11.217 27.20 / 7.331 30.84 / 4.753	23.96 / 11.006 27.20 / 7.867 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 shape-gain transformation for each comparison with the dictionary (we are using a dictionary with 4096 entries) and this slightly 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

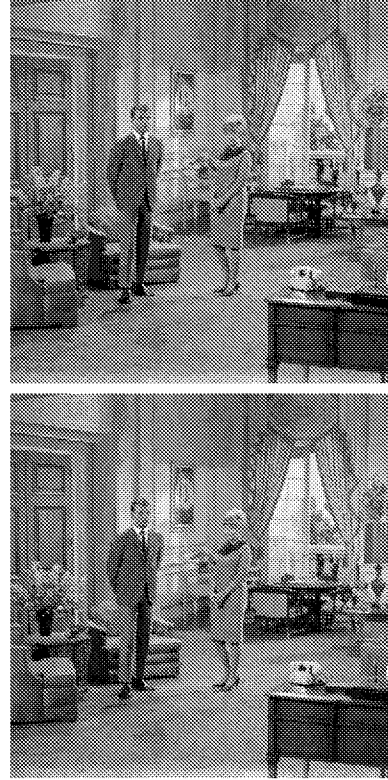


Figure 3: LivingRoom

6. REFERENCES

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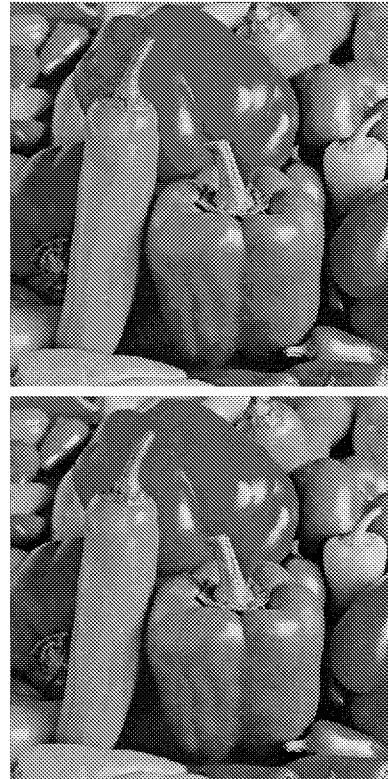


Figure 4: Peppers