Increasing the Error Tolerance in Transmission of Vector Quantized Images by Self-Organizing Map

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Abstract Image compression is needed for image storage and transmission applications. Vector quantization methods offer good performance when high compression rates are needed. Image quality problems may be encountered if vector quantization methods are used in transmission of images through noisy transmission channels, because erroneous codeword will usually be decoded into a whole block of completely erroneous pixels. Image quality can be significantly improved if noise properties are taken into account already in VQ design stage. In this paper it is shown that using the Self-Organizing Map algorithm in vector quantization codebook design one is able to reduce the degradation due to transmission errors.

1. Image Vector Quantization using Self-Organizing Maps

Image compression is needed for image storage and transmission applications [1]. Lately the image compression using Vector Quantization (VQ) techniques has received large interest [2]. In VQ approaches adjacent pixels are taken as a single block, which is mapped into a finite set of codewords. In decoding stage the codewords are replaced by corresponding model vectors (see Figure 1). The set of codewords and the associated model vectors together is called a codebook. In VQ the correlations which exists between adjacent pixels are naturally taken into account, and with a comparatively small codebook one achieves a small quantization error in reconstructed images.

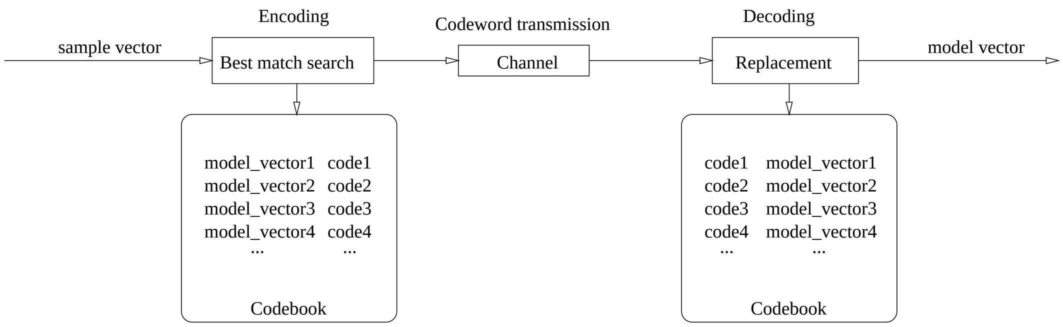

Figure 1: *Vector quantization in image compression application. A sample vector (a subimage) is compared to all model vectors in a codebook and the best matching codebook entry is selected. The corresponding codeword is sent to the transmission channel. In the decoding stage the model vector associated with the codeword is searched from the codebook and used in building a reconstructed image. The two codebooks are identical.*

The main idea in vector quantization is to find a codebook which minimizes the quantization mean error in reconstructed images. One of the best known VQ methods is the Linde-Buzo-Gray (LBG) algorithm [3], which iteratively searches clusters in the training data. The cluster centroids are used as the codebook model vectors, while the codewords for them can be selected arbitrarily.

The Self-Organized Map (SOM) algorithm [4][5][6] has also been suggested for vector quantization [7][8]. In the SOM the weight vectors of the neurons form the codebook while the coordinates of the SOM array can directly be used as the codewords. The distortion errors in using codebooks produced by both the SOM algorithm and the LBG algorithm are rather similar [7][8]; however, in [8], the SOM algorithm was found to be more robust with respect to initialization than the LBG algorithm.

The central difference between the LBG and SOM algorithms, however, is the following. The LBG algorithm does not give any order in the codebook; the codewords for model vectors are selected arbitrarily. Contrary to that, the codebook trained by the SOM algorithm has acquired an internal order; adjacent codebook entries have similar codewords and similar model vectors. This order can be utilized to increase error tolerance.

2. Error Tolerance using Self-Organizing Maps

Assume that a vectorial data item x is converted to some codeword y and then back to the decoded vector x'. If the codeword y is transmitted through a noisy transmission channel, the errors may change y to some other codeword y'. (see Figure 2). When simple, unordered VQ methods are used, the erroneous codeword will usually be decoded into a whole block of completely erroneous pixels.[1]

In an error-tolerant codebook, the degrading effects of the channel errors are minimized by a proper selection of codewords for the model vectors: *With increasing degree of errors in the codewords, the similarity of the decoded model vectors is made to change gradually.* Contrary to error correction methods, the errors in codewords are permitted, but the effects in reconstructed images are minimized.

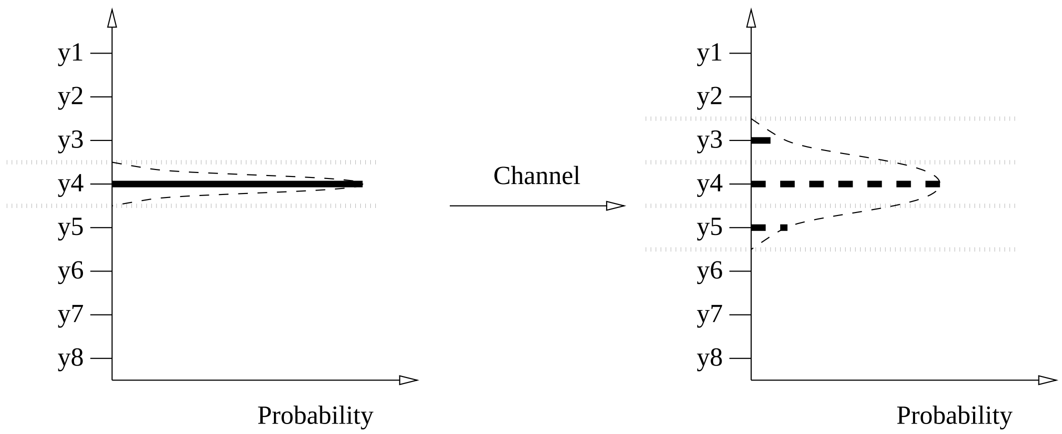

Figure 2: *If transmission channel is imperfect wrong codewords can be detected. Above, an analog signal (code) $y4$ has been sent to channel but due to different errors the signal value can spread over the nearby signal values and it is possible that another signal value (now either $y3$ or $y5$) is recognized. If codewords are multidimensional, similar errors can happen independently in all dimensions.*

In [9] it was shown that it is possible to derive a stochastic gradient descent algorithm for the codebook design for noisy environment. The algorithm (where the training neighborhood was defined through the likelihood of changing the selected codeword to other codewords) turned out to be identical to the Self-Organizing Map training algorithm. *The SOM algorithm therefore leads to a codebook in which the distortion effects are automatically taken into account.*

[1] The errors in codewords are usually corrected by adding error correcting codes into the transmission, preparing for the worst case error conditions. It, however, often increases the required baud rate unnecessarily, because most of the time the transmission channel has less errors.

The benefit of an error-tolerant codebook in data transmission were first demonstrated in [10], in an experiment where speech amplitude values were quantized and random bit substitutions for codewords could happen. The SOM algorithm was used to order the codebook entries. It was shown that the ordered codebook gave a 3 dB reduction in the reconstruction distortion compared to random codeword schemes.

3. Experiments on transmission of VQ images on noisy channels

We have experimented on the effects of transmission errors and their compensation by Self-Organized Maps in image compression (see [11][12]), using codebooks consisting of 512 entries for 4 by 4 pixel subimages.

The following transmission channel models was studied: Each codeword (nine bits long) was divided into three three-bit subwords, each of which was converted into an eight-level analog signal. The signal was assumed to deviate randomly by one level either upward or downward, with a probability of p (see Figure 2).

The codebooks were trained using 28 images of faces (both males and females) and tested using another face image, which was not contained in the training set. All the images were 512 by 680 pixel, 256 gray level images.

Distortion in the decoded images was measured using a peak signal-to-noise ratio (PSNR) defined as:

$$\mathrm{PSNR} = 10 \log \frac{255^2}{\mathrm{MSE}} \text{ dB}, \qquad (1)$$

where MSE is the mean square error.

Topology of the Self-Organizing Maps was selected depending on the channel noise mechanism. For the eight-level transmission channel model a three-dimensional SOM was used, and the three coordinate values of the neurons in the array constituted the codewords. For transmission channel each coordinate value selected the signal level independently. For comparison a randomly-ordered codebook was prepared by relabeling the model vectors. A new, unique random nine-bit codeword was redefined to each.

4. Results

The PSNR values after transmission trough the eight-level transmission channel with different error probabilities are tabulated on Table 1.

Probability p of an error	PSNR in SOM code	PSNR in random code	Difference in PSNRs
No error	34.31	34.31	0.00
0.0001	34.29	33.56	0.73
0.0010	34.15	30.08	4.07
0.0100	32.83	21.94	10.89
0.1000	27.29	12.46	14.83

Table 1: *Peak signal-to-noise rations (in dB) for different levels of noise for eight level channel model.*

In Figure 3 two reconstructed images are shown. The probability for an error was $p = 0.01$. (The probability for an error in a codeword was $P(0.01) = 1.0 - (1.0 - \frac{7}{4} * 0.01)^3 = 0.052$, i.e. more than 5 % of the codewords were changed.) In the image with random order in codewords the errors are usually rather severe; e.g., in the middle of dark areas there are white blocks, and dark blocks in white areas, respectively. In the image with error-tolerant coding the errors are of different nature; for instance, in the dark area the erroneous blocks are never white, but "almost" dark. The subjectively experienced qualities of the images differ significantly,

Figure 3: *The encoded and decoded images after transmission through a moderately noisy ($p = 0.01$) channel. The image with ordered codebook is on the left and the image with unordered codebook is on the right.*

although the same frequencies of errors were present in both of the images.

In Figure 4 another exemplary pair of images is shown. The probability for an error was $p = 0.1$ ($P(0.1) = 0.438$, i.e. almost half of the codewords were changed).

5. Discussion

From the results one can clearly see that degradation of images due to errors in codewords can significantly be reduced if the codewords are ordered. The SOM algorithm can be used to order the codewords automatically. The present simulations demonstrated that the codebooks designed by the SOM are superior to unordered VQ codebooks.

While finishing the paper the author received a copy of a doctoral thesis [13] where the above idea has been studied for speech transmission with good results.

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Figure 4: *The encoded and decoded images after transmission through a very noisy ($p = 0.1$) channel. The image with ordered codebook is on the left and the image with unordered codebook is on the right.*

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