IMAGE COMPRESSION USING HLVQ NEURAL NETWORK

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ABSTRACT

We apply a new neural network: HLVQ combining supervised and unsupervised learning to vector quantization. A supervised learning based on Learning Vector Quantization 2 performs attention focusing over a background of a Self-Organizing Feature Map algorithm. It exhibits the salient features of both algorithms: the topology-preserving mapping characteristic is acquired through unsupervised learning while supervised learning keeps the overlap between classes to a minimum. Pattern labeling is carried out by a separate unsupervised network taking as input the discrete cosine transform of a pattern. First the labelling network is trained on the transform of sub-images. Each neuron of this network is considered as the prototype of one class. Once convergence is achieved, HLVQ is trained. Each sub-image is input to the network. The class of the input pattern is determined by the most activated neuron of the labelling network on presentation of the sub-image transform.

I INTRODUCTION

One of the most important tasks encountered in digital image transmission is the reduction of the amount of information to be transmitted while preserving the quality of the image. Several approaches to image compression (e.g., transform coding, prediction based coding, vector quantization...) have already been proposed. Vector quantization approach has been applied successfully to image compression [1][2]. It exhibits high compression rates and a simple process of decompression. A major difficulty of vector quantization concerns the design of the codebook. It has been pointed out that edge integrity is a key feature when dealing with the visual quality of a reconstructed image [3]. However, it happens that edge blocks are scarcely represented among codewords designed through training since, usually, edge blocks form a small part of the training set. A prominent neural network in the field of image compression is the Self-Organizing Feature Map (SOFM) of Kohonen [4]. SOFM approach presents performances equivalent to that of the LGB quantizer [5]. The SOFM is a "winner-take-all" competitive learning paradigm. The notion of topology is introduced by a neighborhood function governing the number of neurons to be updated. A supervised paradigm based on the previous network has also been designed: learning vector quantization two (LVQ2) [4]. Unlike the former network, LVQ2 focuses on the decision borders in the input space. The winning neuron and its runner-up are updated without consideration for neighborhood. These algorithms use quite a similar updating law. Our new algorithm Hybrid Learning Vector Quantization (HLVQ) takes advantage of both networks by a combination of these learning laws. This paradigm is applied to image compression where supervision provides an efficient mean to tackle the problem of edge-integrity preservation.

II. THE HLVQ NEURAL NETWORK

2.1. Origin of the network

The aim of the HLVQ algorithm is twofold: first, it is designed to self-organize a topology-preserving mapping array of neurons, and second, it oughts to perform well as a supervised classifier. The SOFM algorithm is applied as a background task assigned to every neuron of the map. At the same time, a supervised learning deals with the winning neurons and those of their neighborhoods.

2.2. Description of the learning algorithm

The size of the network and the network dynamic are chosen a priori. The neurons of the map are labelled by a presentation of the training patterns prior to any learning. The maximum number of epochs is chosen large enough to ensure convergence of the network. An epoch corresponds to the presentation and partial

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learning of every pattern in the training set. At the end of each epoch, the patterns are presented without weight adaptation. The winning neuron is recorded for each pattern. A neuron is labellized according to the most represented class among the set of pattern for which is was declared winner. Those for wich no strong majority comes out at the end of this process stay unlabelled. The dynamic of learning is now described. When a pattern x belonging to class Cx is presented, the SOFM algorithm is applied to the winning neuron, i.e., the neuron with maximum activation, and its neirghbor neurons, without consideration for the class of these neurons. Then, the supervised part of the learning algorithm is applied. The winning neuron c of class C_c and its runner-up, i.e., the second winning neuron d of class C_d are identified using a winner-take-all process. The weight updating law is chosen according to the class label of those neurons and that of their neighbor neurons.

2.3. Learning dynamic

Let $\mathbf{w}_i$ be the weight vector of neuron i and $\alpha(t)$ be a learning rate decreasing with time.

- Present a pattern **x** of class C_x,
- If : $C_c = C_x$ and $C_d \neq C_x$, the weight of the winner are updated according to :

$$\Delta\, w_c(t+1) = +\,\alpha(t) * (x - w_c(t))$$

- else :
  - If : $C_c \neq C_x$ and $C_d = C_x$, LVQ2 learning is applied :

$$\Delta\, w_c(t+1) = -\,\alpha(t) * (x - w_c(t))$$
$$\Delta\, w_d(t+1) = +\,\alpha(t) * (x - w_d(t))$$

  - else :
    - If : $C_c = C_x$ and $C_d = C_x$, weights are updated according to :

$$\Delta\, w_c(t+1) = +\,\alpha(t) * (x - w_c(t))$$
$$\Delta\, w_d(t+1) = -\,\alpha(t) * (x - w_d(t))$$

    - else : search for the closest neuron of class C_x in the neighborhood of c and d,
      - if such a neuron e is found, apply :

$$\Delta\, w_e(t+1) = +\,\alpha(t) * (x - w_e(t))$$

      - else : search for an unlabelled neuron in the neighborhood of c and d,
        - if such a nework exists, apply :

$$\Delta\, w(t+1) = +\,\alpha(t) * (x - w(t))$$

        - else : no learning occurs on this presentation of pattern p :

$$\forall i,\, \Delta\, w_t(t+1) = 0$$

- Increase the number of epochs by one.

This dynamic is applied until the maximum number of epochs is reached.

III. IMAGE COMPRESSION

3.1. Why supervised compression ?

As was previously mentioned, the SOFM is the most used neural network in determining the codebook in vector quantization. One of the key features of this network is its ability to approximate the probability density function of the input patterns. When trained on image compression, these patterns are generally issued from slightly textured regions. This leads to the fact that edge patterns are very poorly represented in the learning database. Consequently, most neurons focus on homogenous patterns. While these patterns are numerous in original images, the overall reconstructed-image quality does not depend much on them. In fact, edge-integrity preservation is not achieved by SOFM compression approach. Therefore, the use of a supervised learning approach, based on edge information, is essential in order to improve the edge-integrity preservation on reconstructed images.

3.2. Compression scheme

The compression scheme proposed in this paper is shown in Fig 1. It consists of two major parts: a labelling network (LABSOFM) and a compression HLVQ based network. The LABSOFM uses the transform domain of input sub-images to define different classes to be discriminated. Visual transitions and homogenous regions result in different discrete cosines transforms. An automatic unsupervised analysis of the transform outputs leads to the definition of different classes. One of the main advantages of this method is that the definition of classes is not man-made, i.e., the membership of each input pattern is determined by the clustering process of the unsupervised network. The need of a soft transition between similar sub-images induces our choice of using a SOFM network in this part. Besides, the a priori fixed number of neurons limits the maximum number of classes to be learned by the compression network.

The input sub-image as well as the identification of the corresponding LABSOFM neuron are sent to the compression HLVQ based network. The use of identification LABSOFM neurons ensures that all classes will be represented in the codebook designed by HLVQ and that homogenous regions will not be over-represented.

3.3. Experimental results

The ability of our model to ensure edge integrity is tested on benchmark images. The LABSOFM and HLVQ networks are trained on the same image, namely, "lenna". The LABSOFM is a 5x5 square map using a rectangular neighborhood. The HLVQ network training is delayed until full convergence of the LABSOFM training is achieved. The compression network uses a similar geometry of the map of larger dimension: 8x8. Input sub-images are blocks of 3x3 pixels randomly extracted from a 256 gray-level "lenna" image of 512x512 pixels. According to this random choice of the patterns, the probability density function of the original image is preserved in the training set. The new paradigm is compared to a classical SOFM network using the same map geometry and dynamics as those used by HLVQ network. The initial random weight vectors and the input pattern order are common for both networks.

Fig 2. presents a comparison between an unsupervised SOFM quantizer and the HLVQ quantizer. The enlarged part of the reconstructed image shows a dramatic improvement of edge integrity when using the HLVQ approach. The large amount of 3x3 training blocks ensures a proper approximation of the probability density function by the SOFM algorithm. As show on Fig2.c, the differences between the reconstructed images is mainly localized in edges areas.

Fig 3. represents the compared generalization capability of each approach. As expected, both networks are able to reconstruct the image named "couple" even though none of them was trained on this image. However, some differences appear in the quality of the reconstructed image. Since, the available space does not allow a large scale reproduction of these reconstructed images, the difference image is displayed on Fig 3.b. The large number of edge pixels highlights the improvement stemming from the supervised learning paradigm of HLVQ.

IV. DISCUSSION

Poor edge integrity preservation is a major drawback of unsupervised neural learning of the codebook. This difficulty is overcame by our paradigm through supervision of the training set. The sub-image classes are designed by self-organizing process instead of an a-priori choice [7]. Recent applications of the SOFM paradigm to supervised vector quantization involve one map for each class of patterns, e.g., [8]. Despite promising results, our paradigm exhibits new and salient features when compared to this approach. First, it should be pointed out that there is no connection between neurons of the various maps in [7][8]. During learning, the probability density function is approximated separately for each class. The problems of outliers and borders between classes are not tackled. During compression, a single map is responsible for the coding of an input sub-image, there is neither cooperation nor competition among the maps of the quantizer. Since HLVQ network consists in a single map of neurons, the probability density and the inter-class borders are managed at the same time. When a sub-image is input for compression, each neuron competes with all the others (whether form the same class or not) to code the input. Since a single map is used, optimal distribution of the neurons among the classes is ensured by the SOFM part of the HLVQ paradigm.

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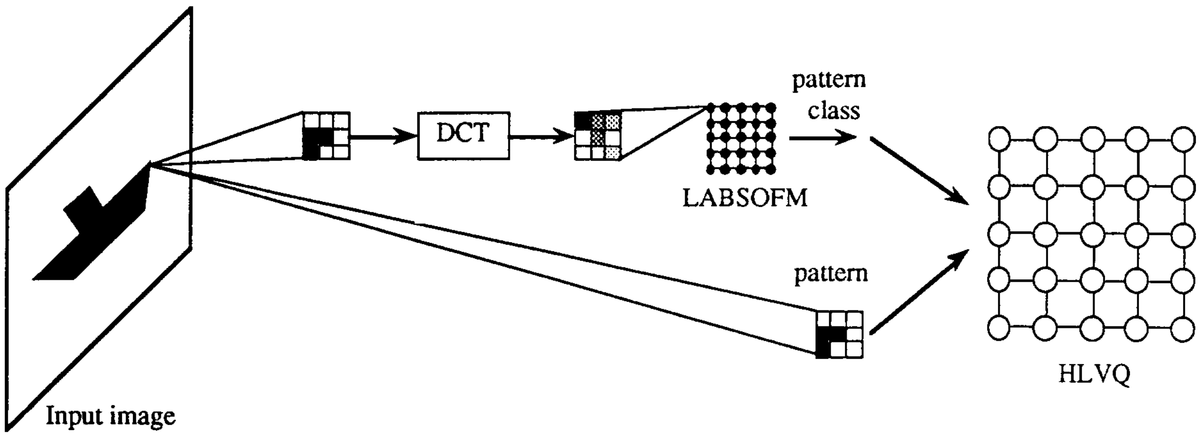

Fig 1.: Architecture of the supervised vector quantizer.

Fig 2: From left to right:
a: reconstructed lenna image using SOFM,
b: reconstructed lenna image using HLVQ,
c: difference image between (a) and (b).

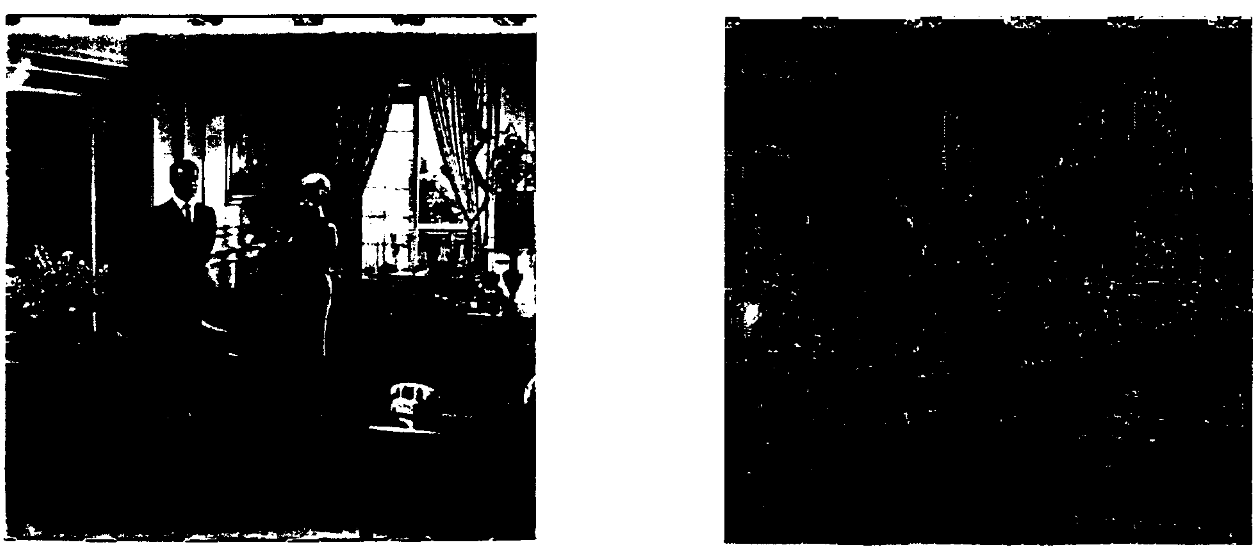

Fig 3: Left : original couple image
Right difference image between reconstrution by SOFM and HLVQ