

Competitive Neural Network Traing: A Multi-resolution Approach

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Abstract

A multi-resolution method for training a Kohonen competitive neural network (KCNN) is presented. Starting with a low resolution sample of the input data, the training algorithm is applied to a sequence of monotonically increasing-resolution samples of the given data. The final weight matrix obtained from a low resolution stage is used as the initial weight matrix for the next stage which is a higher resolution stage. In the average case the multi-resolution reduces the computation time by a factor of more than two with a slight improvement in the quality of quantization. Alternatively it can be used to identify two local optimum solutions at the same time the traditional KCNN finds one local optimum.

Introduction

This paper describes a novel multi-resolution training method for Competitive Neural Networks for vector quantization, (KCNN-VQ) (Kohonen 1984). In the described approach, KCNN-VQ using a low resolution sample of the data set is used to determine the initial weight matrix of KCNN-VQ for a higher resolution sample of the data set.

The objective of this process is to reduce the computational costs of the training process while maintaining the quality of the vector quantization. Alternatively, the probability of getting a solution with better VQ quality is significantly increased.

Several methods for improving the convergence rate of KCNN-VQ are reported in the Literature. These methods include hierarchical VQ, (Luttrell 1991) hierarchical SOM (Lampinen, Oja 1992), and tree-structured SOM (Koikkalinen 1990). The problem with all these methods is that the speed-up in convergence is achieved through a non-recoverable cut in the search space. Hence, several potential solutions are removed from the search space. In contrast, the multi-resolution KCNN-VQ reported in this paper achieves the speed through a better estimation of the initial weight matrix. No solution is excluded from the search space. While a similar method has been applied to the LBG-VQ problem (Tamir 1995), it is the first attempt to apply multi-resolution to KCNN-VQ training.

The CKNN-VQ Training Stage

CKNN-VQ training is an on-line process. An epoch of computation consists of scanning the entire training set randomly or in a fixed sequential order. In each iteration, a vector from the training set is presented to the system. The system updates the weight matrix according to the Kohonen Learning Rule (Kohonen 1984), and “moves on” to the next sampled vector.

Multi-Resolution KCNN-VQ Learning Stage

The multi-resolution procedure consists of the following steps: In the first iteration, the KCNN-VQ procedure is applied to an initial under-sampling of the data. The weight matrix for the first iteration is initialized by any of the traditional methods e.g., random initialization, splitting, or uniform spread. KCNN-VQ is performed on the sample until the calculated weight matrix satisfies the termination condition.

In iteration ' n ', the original data set is re-sampled with twice the resolution of iteration ' $n-1$ '. The weight matrix obtained from the previous iteration is used to initiate the KCNN-VQ of the current iteration.

The procedure is repeated until a resolution of 1:1 is reached. At this stage, the KCNN-VQ algorithm is performed on the entire input data and the resultant weight matrix is reported. The multi-resolution method is referred to as pyramid KCNN-VQ.

The experimental results, presented in the next section, show that while the pyramid KCNN-VQ reduces the convergence time by a factor of two to three the quality of the solution (measured by MSE) is essentially the same as the quality of traditional KCNN-VQ.

Experiments and Results

Two sets of experiments were performed; the first set included synthetic data. The second set used the RGB components of color images to perform VQ for the purpose of object identification. The measures for performance are

computational time and the mean-square-error. The computation time is measured through a weighted number of iterations. The termination condition used in the experiments is achieving a negligible (less than 10^{-6}) improvement in the first derivative of the MSE.

KCNN-VQ algorithm applied to synthetic data

The VQ and multi resolution VQ are applied to a Matlab generates set of eight clusters with 1024 elements per cluster and standard deviation of 0.03 around a random center. Figure 1 compares the results of multi-resolution KCNN to traditional KCNN training using the synthetic data.

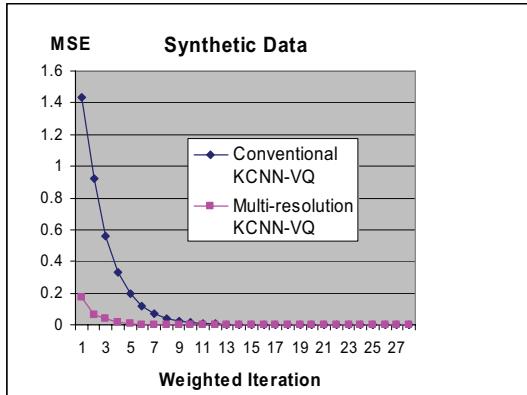


Figure 1 Performance with Synthetic Data

While the KCNN-VQ converged in 29 iterations, the multi-resolution KCNN-VQ converged in 14 weighted iterations. The quality of convergence is virtually identical.

Image segmentation using KCNN-VQ

KCNN-VQ was applied to a set of images in order to segment the images and identify image objects. The KCNN-VQ input is a 24 bit/pixel RGB images, and the output is a set of 16 binary images each of which is used for subsequent connected component labeling and contour following algorithm (Coleman 1979, Tamir 1996).

Figure 2 compares the results of multi-resolution KCNN-VQ to traditional KCNN-VQ training using the image data (using Lena). Similar results were obtained with other images. In these experiments the multi-resolution KCNN-VQ is converging about three times faster than the conventional KCNN-VQ.

Conclusions

The results show a significant (more than 2X) speed-up in convergence time. The quality (measured in MSE) of the

VQ is not changed much. At the same time, due to the convergence speedup, better quality can be achieved via multiple runs of the algorithm with different seeds.

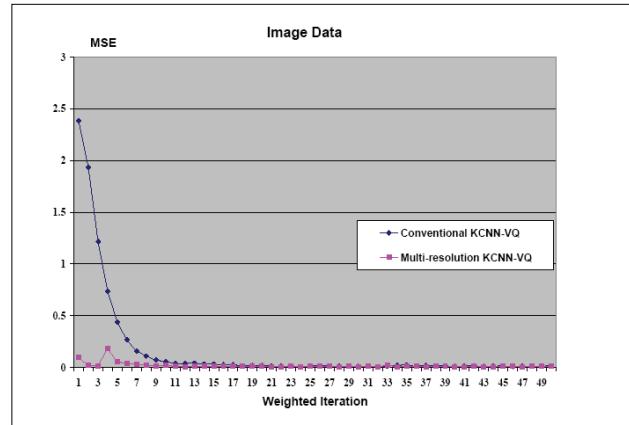


Figure 2 Performance with Image Data

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