VECTOR QUANTIZATION FOR CLASSIFICATION IN A SIMPLE NETWORK[1]

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Gauss mixture models are commonly used in classification due to the robustness and the analytical tractability of the Gaussian distribution. Gauss mixture model-based classifiers can be trained using either the Lloyd algorithm or the expectation-maximization (EM) algorithm. The Lloyd design leads to a Gauss mixture vector quantizer (GMVQ), exploiting various results and techniques from the compression theory.

Both the Lloyd-based design and the EM-based design assume that the data to be classified are available at the classifier. In many applications; however, this is not the case due to channel noise and the constraints on channel capacity. One example is that of a network of sensors, with each sensor sending a noisy version of the data to a common receiver, which is to classify the data based on what it receives. If the channel capacity in the network is limited, the sensors need to send to the receiver the quantized versions of the data instead, requiring the use of a vector quantizer. Our work addresses a special case of this problem where there are two sensors and the noise can be modeled as additive, independent (of the data) and Gaussian.

We design a generalized GMVQ with an encoder at each sensor and a decoder at the common receiver, minimizing the expected quadratic discriminant analysis (QDA) distortion between the original data and the Gauss mixture component, to which it is assigned by the decoder. Each encoder first predicts the index assignment of the other encoder based on its own noisy version of the data. We denote the predicted index of the other encoder by j^p. Then, the encoder assigns its own noisy version to the index i such that the Gauss mixture component associated with the index pair (i, j^p) at the decoder is the one, minimizing the expected QDA distortion. The decoder, upon receiving an index from each encoder, maps the received index pair to the mixture component, minimizing the expected distortion. The quantizer is trained using the Lloyd algorithm, by iteratively updating the encoders and the decoder. Each encoder is updated by predicting the index assignments of the other encoder followed by assigning each noisy input vector to the index, minimizing the expected QDA distortion. The decoder is updated by mapping each index pair to the optimum Gauss mixture component followed by the update of the parameters of each Gauss mixture component.

We have implemented our algorithm on three different data sets: a mixture of Gaussians, a mixture of Laplacians and a a set of aerial of images. For each data set, we observed that the classification performance achieved by our algorithm is very close to the theoretically optimal (Bayes) performance.

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