Improvement of LDPC Slepian-Wolf Coding using Object Disparity Estimation at the Decoder

David Chen
dmchen@stanford.edu

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Distributed coding research aims to achieve optimal compression performance in communicating data between an array of simple devices and a central computer. The distributed devices, such as cameras, have limited hardware and power, so they are subject to two important restrictions. First, they can only use computationally light encoders. Second, even if two of these devices record correlated signals X and Y, the devices do not communicate with one another, which conventionally would be done to facilitate lossless joint encoding at a rate near the joint entropy H(X,Y). Instead, in the distributed coding framework, X and Y are separately communicated to the central computer. Fortunately, the central computer can perform joint decoding of X and Y, and remarkably, based on the result of Slepian and Wolf [1], total lossless communication can still occur at a rate near H(X,Y).

A practical algorithm for encoding a pair of correlated grayscale images at a rate near the Slepian-Wolf limit is given in [2], an extension of the same algorithm for correlated binary images [3]. The image Y is available at the decoder to use as side information in reconstructing the image X. A low-density parity check (LDPC) encoder converts X into a parity bit sequence, and a corresponding LDPC decoder uses expectation-maximization to progressively estimate X based on the fraction of parity bits already received and Y. When the information at the decoder is insufficient for lossless reconstruction of X, the decoder requests that the encoder send more parity bits.

A key feature of the decoder is the incorporation of disparity compensation in expectation-maximization. Since there is usually some spatial disparity between X and Y, disparity-compensated side information is more useful than strictly collocated side information. Significant savings in the required number of parity bits can be obtained by using disparity compensation over the strictly collocated case. Since the disparity is also unknown a priori, disparity estimation is required, and this estimation is currently done on a block-by-block basis for computational tractability.

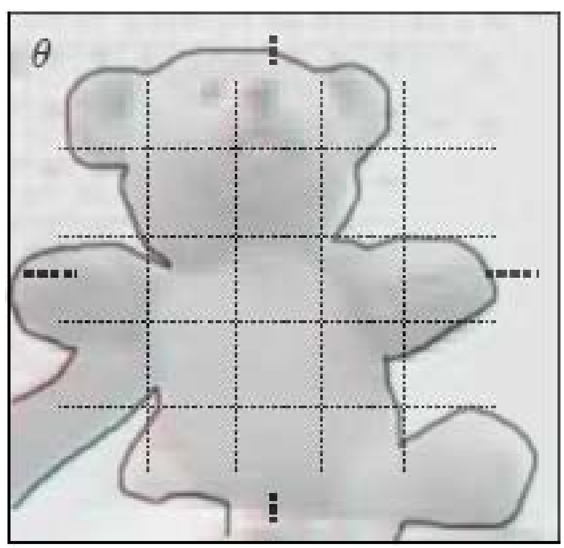

Fig. 1. Segmentation of object into irregularly shaped blocks.

The new project builds on the work in [2] and addresses an important problem yet to be explored. Edges of natural objects generally do not align to rectangular block boundaries, so disparity estimation with reference to rectangular block boundaries may not be as accurate as disparity estimation with reference to true object boundaries. It is proposed that the decoder include an object segmentation module that recognizes objects. Many popular segmentation algorithms can be adapted for this purpose [4], [5]. Once an object's shape has been identified, several different disparity estimation algorithms can be used.

In the first algorithm, the interior of the shape is segmented into blocks, as shown in Fig. 1. Unlike before, some of these blocks are irregularly shaped because they are bounded by segments of the object's true boundary. Block-by-block disparity estimation can be performed as before, except now in terms of the newly defined blocks.

In the second algorithm, the interior of the shape is not segmented into blocks. Instead, disparity estimation is done based on the entire object. More accurate results should be obtained than for the first algorithm, but only at the expense of more computation. For objects much larger than the typical block size, this algorithm may become too computationally burdensome.

Finally, a hybrid algorithm can achieve a good tradeoff between estimation accuracy and computation time by adaptively switching between the first two algorithms. If, say, the object is very large, the first algorithm is selected, but if the object is only moderately large, the second algorithm is chosen. The project will implement these different disparity estimation algorithms and compare their relative coding efficiencies and computation times.

References

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