Distributed Source Coding Using Raptor Codes for Hidden Markov Sources

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Interest in distributed source coding (DSC) has increased in recent years due to the development of wireless networks. In this paper we propose a solution based on a new rateless class of codes, the Raptor codes [1]. In real applications (where the data source length and the correlation between the sources may vary), rateless codes can be naturally adapted by generating just a single codeword with suitable length. Raptor codes were already considered in [2] for the lossless compression of a single source.

The contribution of this work is in showing how it is possible to adapt Raptor codes for the DSC problem, when the sources have memory that can be modeled as Hidden Markov Processes (HMPs). The correlation between the sources does not have memory, while the sources are modeled as HMPs. We consider a systematic version of Raptor codes. In this way the solution can be designed using a “parity-like” approach. We modify the decoding process by implementing a message passing algorithm between the decoders at each iteration. To exploit the source redundancy, we use the trellis describing the HMP as an additive decoder that iteratively exchanges information with the Raptor decoder. This provides better performance in terms of bit error rate (BER). The simulations are carried out considering different hidden and non-hidden (MP) 2-state Markovian models (HMP\textsubscript{1} with \(a_{0,0} = a_{1,1} = 0.35, b_{0,0} = b_{1,1} = 0.05\) and HMP\textsubscript{2} with \(a_{0,0} = a_{1,1} = 0.75, b_{0,0} = b_{1,1} = 0.05\); MP\textsubscript{1} with \(a_{0,0} = a_{1,1} = 0.3\) and MP\textsubscript{2} with \(a_{0,0} = a_{1,1} = 0.65\)).

In Fig. 1a, we fix the compression ratio equal to 2. We estimate the performance for different values of the conditional entropy rate \(H(X|Y)\), where \(X\) and \(Y\) denote the correlated sources. To obtain \(H(X|Y) = 1/2\) for all the different models, the correlation between the sources must change. In Fig. 1b, we show the results obtained by using our solution in rateless mode. We set the conditional entropy rate to \(H(X|Y) = 1/2\) and we estimate the performance as the compression ratio decreases. It is interesting to note that the performance of the different models considered are similar: using a fixed compression ratio (Fig. 1a), we obtain a low BER when \(H(X|Y) \approx 0.4\), while fixing \(H(X|Y)\) (Fig. 1b), we obtain a low BER when the compression ratio is \(\approx 1.7\). This means that the proposed solution is influenced only by the actual value of the conditional entropy rate.

Fig. 1: (a): BER versus conditional entropy rate; (b): BER versus compression ratio.

REFERENCES


This research was supported in part by the U.S. National Science Foundation under Grants ANI–03–38807 and CNS–06–25637