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Universal Decoding Using a Noisy Codebook

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Abstract

We consider the topic of universal decoding with a decoder that does not have direct access to the codebook, but only to noisy versions of the various randomly generated codewords, a problem motivated by biometrical identification systems. Both the source that generates the original (clean) codewords, and the channel that corrupts them in generating the noisy codewords, as well as the main channel for communicating the messages, are all modeled by non–unifilar, finite–state systems (hidden Markov models). As in previous works on universal decoding, here too, the average error probability of our proposed universal decoder is shown to be as small as that of the optimal maximum likelihood (ML) decoder, up to a multiplicative factor that is a sub–exponential function of the block length. It therefore has the same error exponent, whenever the ML decoder has a positive error exponent. The universal decoding metric is based on Lempel–Ziv (LZ) incremental parsing of each noisy codeword jointly with the given channel output vector, but this metric is somewhat different from the one proposed in earlier works on universal decoding for finite–state channels, by Ziv (1985) and by Lapidoth and Ziv (1998). The reason for the difference is that here, unlike in those earlier works, the probability distribution that governs the (noisy) codewords is, in general, not uniform across its support. This non–uniformity of the codeword distribution also makes our derivation more challenging. Another reason for the more challenging analysis is the fact that the effective induced channel between the noisy codeword of the transmitted message and the main channel output is not a finite–state channel in general.

Index Terms: Universal decoding, finite–state channel, hidden Markov model, Lempel–Ziv algorithm, error exponent.