Chapter II
Is Entropy Suitable to Characterize Data and Signals for Cognitive Informatics?

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ABSTRACT
This chapter provides a review of Shannon and other entropy measures in evaluating the quality of materials used in perception, cognition, and learning processes. Energy-based metrics are not suitable for cognition, as energy itself does not carry information. Instead, morphological (structural and contextual) metrics as well as entropy-based multiscale metrics should be considered in cognitive informatics. Appropriate data and signal transformation processes are defined and discussed in the perceptual framework, followed by various classes of information and entropies suitable for characterization of data, signals, and distortion. Other entropies are also described, including the Rényi generalized entropy spectrum, Kolmogorov complexity measure, Kolmogorov-Sinai entropy, and Prigogine entropy for evolutionary dynamical systems. Although such entropy-based measures are suitable for many signals, they are not sufficient for scale-invariant (fractal and multifractal) signals without corresponding complementary multiscale measures.

Introduction
This chapter is concerned with measuring the quality of various materials used in perception, cognition and evolutionary learning processes. The multimedia materials may include temporal signals such as sound, speech, music, biomedical and telemetry signals, as well as spatial signals such as still images, and spatio-temporal signals such as animation and video. A comprehensive review of the scope of multimedia storage and transmission is presented by Kinsner (2002). Most of such original materials are altered (compressed or enhanced) either to fit the available storage or bandwidth during their transmission, or to enhance perception of the materials. Since the signals may also be contaminated by noise during different stages of their processing and transmission, various denoising techniques must be used to minimize the noise, without affecting the signal itself (Kinsner, 2002). Different classes of coloured and fractal noise are described by Kinsner (1996). The multimedia compression
is often lossy in that the signals are altered with respect not only to their redundancy, but also to their cognitive relevancy. Since the signals are presented to humans, cognitive processes must be considered in the development of suitable quality metrics. This chapter describes a very fundamental class of metrics based on entropy, and identifies its usefulness and limitations in the area of cognitive informatics (CI) (Wang, 2002).

## Issues in Compression and Coding

A simple source compression consists of taking an input stream of symbols $S$ and mapping the stream into an output stream of codes $G$, so that $G$ should be smaller than $S$. The effectiveness of the mapping depends on the selection of an appropriate model of the source. This two-step process is illustrated in Figure 1.

Modelling of the source is intended to extract information from the source in order to guide the coder in the selection of proper codes. The models may be either given a priori (static) or may be constructed on-the-fly (dynamic, in adaptive compression) throughout the compression process. In data compression, the modeller may either consider the discrete probability mass function (pmf) of the source, or look for a structure (e.g., the pattern of edges and textures) in the source itself. In perceptual signal compression, the modeller may consider the perceptual framework (e.g., edges and textures in images and the corresponding masking in either the human visual system, HVS, (Pennebaker & Mitchell, 1993) or the human psycho-acoustic system, PAS (Jayant, 1992). It is in this modelling that CI ought to be used extensively.

A simple data source coder minimizes the bit rate of the data by redundancy minimization based on Shannon first-order or higher-order entropies. Redundancy is a probabilistic measure (entropy) of the spread of probabilities of the occurrence of individual symbols in the source with respect to the the equal (uniform) symbol probabilities. If the probabilities of the source symbols are all equal, the source entropy becomes maximum, and there is no redundancy in the source alphabet, implying that a random (patternless) source cannot be compressed without a loss of information. The objective of the lossless compression techniques is to remove as much redundancy from the source as possible. This approach cannot produce large source compression. The quality of an actual code is determined by the difference between the code entropy and the source entropy; if both are equal, then the code is called perfect in the information-theoretic sense. For example, Huffman and Shannon-Fano codes (e.g., Held, 1987, and Kinsner, 1991) are close to perfect in that sense. Clearly, no statistical code will be able to have entropy smaller than the source entropy.

On the other hand, a perceptual source coder minimizes the bit rate of the input signal, while preserving its perceptual quality, as guided by two main factors: (i) information attributes derived from the structure in the given source (e.g., probabilities related to frequency of occurrence or densities, as well as edges and textures related to the singularities in the signal), and (ii) features derived from the perceptual framework (e.g., masking in the HVS and PAS). This corresponds to the removal of both redundancy and irrelevancy, as shown by the Schouten diagram in Figure 2. This orthogonal principle of both redundancy reduction and irrelevancy removal is usually difficult as it does not correspond to the maximization of signal-to-noise ratio, SNR (i.e., the minimization of the mean-squared error, MSE), and is central to the second-generation of codecs. For example, an edge of an object

*Figure 1. Compression is modeling and coding.*