Neutrosophy for physiological data compression:in particular by neural nets using deep learning

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Abstract

We would like to show the small distance in neutropsophy applications in sciences and humanities, has both finally consider as a terminal user a human. The pace of data production continues to grow, leading to increased needs for efficient storage and transmission. Indeed, the consumption of this information is preferably made on mobile terminals using connections invoiced to the user and having only reduced storage capacities. Deep learning neural networks have recently exceeded the compression rates of algorithmic techniques for text. We believe that they can also significantly challenge classical methods for both audio and visual data (images and videos). To obtain the best physiological compression, i.e. the highest compression ratio because it comes closest to the specificity of human perception, we propose using a neutrosophical representation of the information for the entire compression-decompression cycle. Such a representation consists for each elementary information to add to it a simple neutrosophical number which informs the neural network about its characteristics relative to compression during this treatment. Such a neutrosophical number is in fact a triplet (t,i,f) representing here the belonging of the element to the three constituent components of information in compression; 1° t = the true significant part to be preserved, 2° i = the inderterminated redundant part or noise to be eliminated in compression and 3° f = the false artifacts being produced in the compression process (to be compensated). The complexity of human perception and the subtle niches of its defects that one seeks to exploit requires a detailed and complex mapping that a neural network can produce better than any other algorithmic solution, and networks with deep learning have proven their ability to produce a detailed boundary surface in classifiers.

Keywords: Compression; physiological data compression; neural nets; Neutrosophic; deep learning

1 Introduction

Here we would like to emphase the incidence of the human aspect present in every application, and therefore in any theory. In the end, every development address directly or indirectly on a more close or further relation a human user. The physical specificities of the human being as a user, also on the cognitive side, are quite well defined and relatively homogeneous. Therefore the applications, developments and theories can be suited, tailored, to take into account those characteristics for optimization. In our current case, we consider an improvement to data compression adapted to human perception such as in hearing of seeing. Based on the closeness of human cognition/perception with artificial intelligence inspired by neural networks, we propose a narrower adaptation to the human receiver through the highly-performing deep-learning methods with now adding the potential of the 3-state approach of neutrosophy, that we believe is closer to human cognition than classical binary logic, and also closer to the compression process itself.

More and more data is produced, then transmitted and stored. In both cases a compression of this data allows to optimize these operations in cost and time. The main types of data are text, sound, images and videos, in ascending order of sizem as well as compression potential. Currently videos are the most used by the majority of people. This data is often accessed on mobile devices such as smartphones that communicate through a user-charged connection- Also, their solid-state memory storage is more expensive than traditional hard disks. Thus, more efficient compression methods would bring significant advantages on both levels (transmission and storage).

Two main categories of compression are considered according to usage: lossless compression and lossy compression. Lossless compression fully restores initial information after decompression. A theoretical limit to the compression ratio is given by Shannon's theorem [1]. Lossy compression produces better compression rates at the cost of information loss: decompression produces only a degraded version of the original information. However, losses can be intelligently directed mainly towards limitations of human perception (and also to less relevant data). This type of compression. Physiological (adapted to the imperfections of the human physiology), is used when the information is intended for a human being who will receive it through his perceptive system, mainly auditory and visual. Thus a certain deterioration of the message is admissible, and it can even pass completely unnoticed. Sometimes some perceptible degradation is even tolerable and higher compression rates can be achieved.

In such lossy compression the decompressed information differs from the original information in three ways: (1) some initial elements important to the human receptor have disappeared, (2) other elements have also disappeared but are not important to the human receptor, and, as a result of treatments performed to best eliminate this second category, (3) parasitic elements (called artifacts) are unfortunately introduced into the decompressed information. In the first case there is degradation by loss of content, in the second case there is compression by voluntary deletion of insignificant content, and in the third case there is degradation by disturbance. A good compression technique is characterized by maximizing category 2 with simultaneous minimization of categories 1 and 3. Often compression methods allow compression and degradation to be exchanged according to the objectives sought, favouring one or the other.

Text compression exploits the existing dependency between one symbol and the following ones (character, word, sentence, paragraph). The audio compression also, and more often performs a transformation to the frequency domain where this redundancy is more apparent, and therefore easier to exploit. For images, the redundancy to be eliminated is sought spatially and sometimes hierarchically, but a frequency transformation is often exploited too. Finally for the videos a temporal redundancy is also exploited, an image of a film varying only little from the previous one.

Neural networks, especially those with a large number of layers (deep learning), most often act by detection, classification, transformation of representation space when it is not directly by coding and compression. Thus they reproduce the major features of compression methods. In particular for the image processing they realize an automatic identification of the most significant characteristics which is the typical operation of an encoding with optimal compression.

2 Current research

Although little has been found in the literature, recent research on deep multilayer neural networks, known as deep learning, has also focused on compression techniques and new methods have been proposed for both lossless and lossy compression. In general, these networks have the potential to discover relatively hidden relationships and exploit them to reduce redundancy as compression requires. In the second category their advantage would also be to better exploit the limits of human perception and thus to adjust compression as close as possible both to what is most important for the observer and to that, while being parasitic, disturbs him the least. The adaptation to the physiology of human perception can be pushed further than with algorithmic methods. Another positive point is their ability to perform sub-optimal processing at a much lower cost than full processing (algorithmic), and even to exploit fast vector or matrix processors existing in graphics rendering systems present even on low-end mobile phones. Builders of such graphics systems have begun to produce such architectures optimized also for deep learning, counting on the rapid emergence of this field.

In the most demanding field of lossless text compression, the method proposed by Tatwawadi [2] exceeds existing compression methods for complex corpuses such as chromosome data with a compression ratio of 82.5% versus 76.2% for the most used gZip compressor (free version with GNU license of Zip, derived from LWZ, itself an extension of LZ78 due to Jacob Ziv[3] and my prominent former colleague Abraham Lempel at HP Labs). Let us also note that the best result achieved for the compression of the Wikipedia encyclopedia, compression ratio of 84.6%, is obtained by another deep learning neural network technique choosing the best result among 2000 competing compressors [4], of which the one proposed by this reference is significantly close at 83.2%.

For the most commonly used type of compression, lossy compression, few experiments have been performed. In the case of images, preluding the largest category in quantity: video, mixed techniques are also used. They consist in mixing a preprocessing by neural networks with a usual image compression algorithm such as JPEG. For test images the similarity to the original was measured for an identical compression ratio, the method proposed by Harshavardhan [5] produces the best quality, the similarity measurement varying from 0.82 to 0.89 with an average of 0.85 against 0.75 for JPEG. This method also has the advantage of low computing costs and parallel implementation (distribution over several processors).

3 Proposal

In addition to the use of deep learning neural networks for lossy and lossless compression, we propose the introduction of a treatment based on a neutrosophical approach for lossy physiological compression. By using the model of neutrosophical representation of the data to be compressed, deep learning can be directed towards a more optimal treatment in the sense of the maximisation (2) and the minimisations (1 and 3) mentioned above, thus taking better account of the physiology of human perception and making the most of its weaknesses.

Note that Kuwar [6] has already successfully experimented with the use of convolutional deep learning neural networks to reduce artifacts introduced by JPEG compression in the frequency domain.

A neutrosophical approach is to consider information no longer in a precise and binary way, but fuzzy and ternary. By fuzzy we refer to fuzzy logic [7] where a value is not 0 or 1 but may be 0 with some membership function and 1 with some other membership function. By ternary we mean a representation of three states: true state, false state and undetermined or neutral state. This last state, neutral, gave its name to neutrosophy, which was originally a philosophy, but which developed by extending its central logical aspect into a mathematical one. This philosophy corresponds more to the human way of thinking, and this mathematics is more general than that of binary logic (the one of first order predicates) as well as that of fuzzy logic (and includes them as special cases). We return in more details to neutrosophy in the next section.

Indeed, if human cognition is neutrosphic, that is, its way of thinking consistently implies the use of a neutral state, then so is its perception. All human reflection is not only rational, i.e. logical, but is also influenced by affective aspects. Every reflection is tinged with judgment, both in its result and first of all in its premises and steps. Behind every elementary idea there is closely associated an affect, which is a value judgment: I like it, I do not like it or I am indifferent, that is to say neutral. The affect or judgment is neutrosophical in nature, ternary, with an important neutral aspect because it is frequent.

In any act of human perception, part of the information continues its way into the human brain system, while another part is more or less actively rejected and the rest is ineffective, neutral. It is also so in the various subsequent processing steps.This is in fact a semantic extraction (not to say a compression) seeking to isolate the relevant according to the context by rejecting what is determined not significant according to this same context, and the rest which is declared neutral.

We mentioned earlier the three aspects of compression on a physiological basis which is to detect the most significant, to ignore the neutral, but also to reject noise, the non-relevant. The orientation towards these three functions - detection, deactivation (passive), rejection (active) - of learning (and preception and cognition and compression) can be produced by a neutrosphic representation of the information throughout the processing by the neural network according to the three neutrosophic states: meaning, to be reject or neutral. Thus the network will organize itself more efficiently and more rapidly towards the three joint functions of optimal physiological compression: selection of what is significant for the human receptor, rejection of disturbuing artefacts produced by extreme compression in the non-physiologically perceptible, and elimination of all that is neutral for the human receptor. Then the mechanism of compression can be pushed to its limits given human perception.

4 Some information about neutrosphy

Recent trends in the use of neutrosophy can be found in the reference work edited by Smanradache and Pramanik entitled "New trends in neutrosophical theory and its applications" [8].

As previously mentioned, the inspiration for the neutrosophical representation of reality derives from the philosophy called neutrosophy. This representation is general and makes possible to unify in particular the various apparently very distinct logic variants: classical logic, also called binary logic or Bool's logic, fuzzy logic and its various varieties, and itself, a three-state logic, characterized by a neutral state [9].

In summary, instead of a logical value with two crisp states 0 or 1, the neutrosophical approach considers a representation by a triplet (t.i,f) where these three real values t, i and f represent the equivalent of probabilities for truth (t), indetermination or neutral state (i) and falsity (f) respectively. We prefer to speak of belonging functions according to the vocabulary used in fuzzy logic. These three values are between 0 and 1. Thus, the two classical binary logic values 0 and 1 are represented respectively by (0,0,1) and (1,0,0). Now a simple probability p of having the value 1 and therefore (1-p) of having the value 0 is represented by (p,0,1-p). In this particular case the neutrosophical representation mainly brings a general formulation (just like for a binary value), and thus it also makes possible to represent this conception which it encompasses in its generality (also for fuzzy logic and its numerous varieties of which the so-called "intuitionistic" one).

Operations on neutrosophical triplets, preferably called simple neutrosophical numbers (for simple value, in the sense of mono, a single triplet), can be defined in various ways, either by using arithmetic operators (e.g. multiplication for logical-AND) or functional operators (such as minimum, maximum, etc). For example the complement of (t,i,f) can be defined as (f,1-i,t), but other conventions may be more appropriate depending on the applications. Let us return now on the preceding case of an operator with two operands, as the logical AND mentioned before, let us consider this time the logical OR, i.e. the union together. For two simple neutrosophical numbers A and B represented by the triplets (t_a,i_a,f_a) and (t_b,i_b,f_b)then their union A OR B will be the triplet $(\max(t_a,t_b), \max(i_a,i_b), \min(f_a,f_b))$.

Although a neural network is self-organisîng according to a learning algorithm cleverly elaborated and parameterised to use internally representations adapted to the problem to be solved, in particular it can carry out a change of reference, a projection and other operations that can be geometrically illustrated. This autonomous organisation is however costly in terms of learning time but also in terms of the quality of the performance produced. If, for a given application, it is known that a representation is generally chosen for powerful classical algorithms, then it is highly likely that the network will choose a similar representation, a relatively close one. Indeed often for a specific application it is preferable to start from a network pre-trained on a problem either more general or rather close, which precisely means to start from a relatively appropriate representation.

Then the neutrosophical representation can be precisely one of these representations appropriate for a class of problems considered. And we postulate that this is the case for lossy physiological compression.

5 Physiological compression based on neutrosophical representation

As highlighted in the presentation of our proposal, lossy cuts are essentially adjusted in the case of a human receptor. It can be for example an audio content, an image, or a video sequence. At the end of the processing, storage and transmission chain there is a human user who will receive the message after decompression. This message carries a semantic content which is the most important, it must be perceived by the human receiver through his capacities of perception, mainly auditory and visual. However, human perceptual systems are not perfect and have a number of defects (more than a hundred for vision, the best known of which are optical illusions) that are generally not disturbing for the proper perception of common messages.

These defects have the advantage that they can be exploited in the overall organization of the compression process. And this in two ways: first, it is useless to transmit what cannot be perceived and it should therefore be deleted during compression. But also the involuntary residues of compression, the artefacts, must be organized to preferentially be located in these "blind" zones, orat least the less sensitive ones.

By training on appropriate examples, neural networks can learn to optimize these two situations, just as they are able to detect what is important, for example in speech recognition or artificial vision.

As we are in the presence of three components of the original information: (1) the significant, (2) the insignificant neutral and (3) the disturbing, and as we want to exploit this decomposition for compression, more exactly to realize this decomposition in those three components (or close to). Then to increase the performance of the neural network and facilitate its learning it is preferable to work entirely according to these three components, that is to say according to a neutrosophical paradigm. So the network does not have to discover this helping organization; we give it as a starting and working orientation.

For example, consider the case of image compression. The first step would be a pre-treatment to transform it into a neutrosophically represented image for the purpose of physiological perception. For each pixel of the image conventionally represented by an RGB triplet (red, green, blue), it would be productive to convert it in a more significant color space like HLS (Hue, Luminosity, Saturation) then to add the neutrosophical triplet (t,i,f). The three neutrosophical components t, i and f would then have the significance of probabilities of belonging to the meaningful part of the image, respectively to the potentially irrelevant one and most drastically compressible part, but also to a potential artifact zone. These three values t, i and f could be initialized by specific networks of significant content detection, semantic "noise" zones, and zones potentially tainted with compression artifacts. An additional (pre)treatment would be to move in the frequency domain (other representation) by a transformation of the FFT type, even it can mean letting the network treat jointly the two domains: the spatial and the frequency one.

The Fig. 1 illustrates examples of artifacts produced by compression. Note the "shadow" of the balloon in the sky, and similarly the edges of the star after magnification.

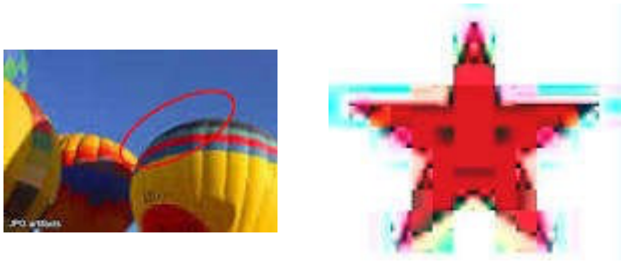

Figure 1: Examples of compression artifacts

Such an artifact is more visible when located in a quiet area of the image. This area can be identified by a neural network using deep learning and corrected during decompression at the cost of a small additional amount of data. It can potentially be partly counterbalanced before, during compression. Image segmentation and other content extraction operations performed efficiently by neural networks exploited for artificial vision can help to delimit the most significant areas and by complement (or preferably by specific processing) the least significant areas.

Finally, this triple process of accentuation of the significant, reduction of the non-significant as well as compensation of the artefacts produced (or to occur) can be carried out in a dynamic way throughout the compression process. Thus the neutrosophical representation of the information is exploited throughout the processing of compression, conducted in a physiologically adapted manner. In total, it must be possible to achieve a higher compression ratio than with other methods because it will include physiological aiming (thanks to neutrosophical representation) at the heart of the compression process.

Conclusion

On the basis of works demonstrating the performance of neural networks using the deep learning paradigm for lossless text and lossy image compression, we recommend to preferentially consider such solutions for other types of compression whatever audio and video as well.

In such cases of data reduction high compression ratios can be achieved when the receptor is human and the compression can be adjusted to its physiological abilities of perception. We postulate that neural networks of the deep learning kind are the most optimal solution to such a multi-criteria fine tuning (problem equivalent to multi-criteria classification).

Moreover, we propose to use a neutrosophic representation of the information throughout the compression-decompression process because its three components of belonging forming the triplet (t, i ,f) make it possible to direct such networks towards the triple representation both characteristic of lossy compression and the physiology of human perception, from which the former actually derives. The first component t then corresponds to the information truely significant for the human receptor (and in a relatively equivalent manner for a network working on recognition applications), the second noted i corresponds to what can be the most highly compressed because it is the least significant (neutral) according to human physiology (and also, by making a complementary use of the detection capabilities of the network, as content), and respectively the third noted f denoting as falsity all that is artifact potentially produced by the compression process itself (which can be learned by a network).

The whole process of compression-decompression is to be considered in the neutrosphical representation to leave to the network the possibility of exploiting compression on a physiological basis at best.

We believe that this is realistic in the short term because of the hardware vector processing accelerators available, even in mobile phones, and that higher compression ratios, respectively at equal ratio better fidelity, can be achieved.

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