Images Compression for Medical Diagnosis using Neural Networks

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Abstract

Images compression is a widely studied topic. Conventional situations offer variable compression ratios depending on the image in question and, in general, do not yield good results for images that are rich in tones.

This work is an application of images compression of patient's computed tomographies using neural networks, which allows to carry out both compression and decompression of the images with a fixed ratio of 8:1 and a loss of 2%.

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Introduction.

Most of the phenomena studied in Medical Sciences, caused both by pathological and normal processes, have morphological basis, expressed with images able to define the degree or intensity of the phenomena, as well as their temporal variations.

Technological advances have facilitated the development of new medical fields, such as diagnosis through images, which make possible a more complete study of the patient with non-invasive methods.

These methods range from simple x-ray radiographies (XR) to more complex techniques such as echographies, computed axial tomographies (CAT), magnetic resonance (MR), etc., all of them directly or using contrast substances.

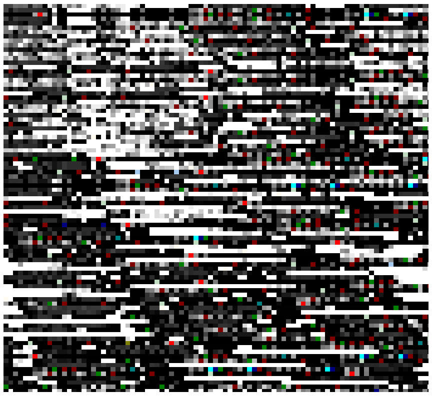
The study of an only image allows to obtain valuable data both for diagnosis and certain treatments: a dental XR allows to diagnose lesions and to adopt a specific treatment (extraction of the dental piece for example) or even to identify individuals. A CAT of the cephalic extremity allows to diagnose a lesion or a cerebral or cranial pathology, and to establish a treatment accordingly.

In these cases, the diagnosis is carried out based on qualitative or quantitative variations and on the values of certain parameters which include a great amount of measures: distance between anatomic elements, shapes, sizes, and amplitude of some organs or lesions, and their relationship with neighbouring structures. Based on the analysis of the images, physicians establish a probable diagnosis to infer a prognosis and decide on a treatment.

These important benefits offered by image diagnosis, are complemented with the huge importance of the method for an evolutive study of lesions or diagnosed pathologies.

Thus, it is possible to quantify the magnitude of the changes, as well as the speed at which they are produced, therefore establishing both the malignity degree and the seriousness of the process or the effectiveness of a treatment.

This evolutive study is only possible through the comparison of different images taken at different times; therefore, it is necessary to count with a suitable images filing system.



Let us consider the figure on the left as an example. Here it is possible to define the location of the cut planes where measures are taken, and to obtain benefits from these measures such as: determine the thickness of the bone, of the plaster cap, or of any other identifiable osseous element, osseous density, shape and size of lateral cerebral ventricles, cephalic mass density, shape, disposition and direction of the optical nerve, etc.

Different images of the same individual at different ages would allow to compare these parameters (ontogenetic development) or the analysis of an evolutive pathologic lesion; the availability of images from other individuals would allow philogenetic studies or studies of a given population.

In any of these cases, it is necessary to be able to retrieve the filed images with a maximum degree of accuracy, since the comparison of the values of the parameters used would allow to establish a correlation, which is fundamental for diagnosis.

Objective:

The use of the backpropagation neural network model applied to the compression of images of computed tomographies, formed by three layers, is proposed. This model uses supervised training based on learning through correction of the error between the expected and the obtained outputs. [RAO][PAO]

Since we are looking for an algorithm allowing the compression and decompression of an image, the input pattern is located on the ends of the network and the neurons of the hidden layer are used to represent compression.

This means that once the training stage is finished, the use of the network consists in the duplication of the hidden layer and in the use of

- the input layer and the hidden layer to carry out the compression process, and
- the hidden layer and the output layer to carry out the decompression process.

Analysis of the Neural Network used:

Backpropagation Network:

A backpropagation network - which is designed to work as a multilayer network - was used, with a supervised learning method.

A backpropagation network is a correspondance network; that is, it allows the calculation of a functional relation between input and output. Each input pattern is associated with its corresponding output pattern.

Training:

The network learns a pre-defined set of input and output pairs by using a two-phase propagation-adaptation cycle.

The input vector is applied to the first layer and is propagated through the upper layers until it reaches the output layer. The output signal is compared to the desired output, and an error signal is calculated for each unit of the output layer.

Output signals are transmitted backwards, in the direction of the nodes of the intermediate layer that directly contribute on the output layer.

The nodes of the intermediate layer receive a fraction of the error proportional to their contribution to the output value.

Based on the error signal perceived, connection weights for each unit are updated in order to make the network converge towards a state which will allow to code training vectors.

The equations used are the following:[KOS][RAO][PAO]

The input pattern $X_p = (x_{p1}, x_{p2}, ..., x_{pN})$ is applied to the input units.

Net inputs for the hidden layer are calculated

$$\sum \qquad + \theta$$

Outputs are calculated for the hidden layer $i_{pj} = f_j^h(neta_{pj}^h)$

Neurons net values of the output layer are calculated

$$neta_{pj}^o \quad \sum_{j}^{L} w_{ki}^o \, i_{pj} + \theta_k^o$$

$$o_{pk} = f_k^o(neta_{pk}^o)$$

$$\delta^{o}_{pk} \quad (y_{pk} - o_{pk})\ f^{'o}_{k}(neta^{o}_{pk})$$

$$\delta \qquad\qquad \imath^{k}_{pj} \ \sum \delta^{o}_{pj} w^{c}_{k}$$

$$) + \eta\ \delta$$

$$) + \eta\ \delta$$

$$f \ \ x \qquad \frac{1 - e^{-x}}{e^{-x}}$$

The purpose of network training is to take the weights of the connections between the neurons towards values which will minimize the error representing the difference between input and outout patterns.

That is, the following expression is minimized

$$\sqrt{\sum \qquad do - val}$$

until it reaches the desired tolerance. Such value is in direct ralation to the quality of the image to be obtained, since an increment of the error tolerance value will result in a lower convergence time, as well as in a greater loss in the image.

Also, it should be noted that the compression ratio of the method here proposed is independent from the image, since it is perfectly determined based on the size of the hidden layer.

Results obtained:

Initially, a network with 128 neurons on the intermediate layer, 512 on the input layer, and 512 on the output layer was considered, that is, a 4:1 compression. Later, a prooning technique was used until the intermediate layer was reduced to 64 neurons, that is, a compression ratio of 8:1 without affecting the tolerance sought, nor increasing convergence time too much.

A set of 20 images of computed tomographies was used to build up the training patterns archive. Each image was divided in 8x8-pixel blocks, each corresponding to a pattern. This patterns archive was built with an only sample of each type, which eliminates the weight of repeated patterns, thus allowing every pattern to be learnt with the same intensity, which in turn reduces convergence speed.

The use of representative images as a way of obtaining the training patterns allows a reduction of convergence time. However, this process implies that if the type of images to be compressed is changed, or if the amount of images to compress is increased, a re-training will be necessary.

The tests carried out allowed to obtain an error of 0.01 after training, with approximately 100 iterations over the input patterns set.

The value of η used was 0.01, since the tests carried out detected a higher value that could produce oscilations in the convergence of the network, thus increasing training time.

In this case, the tendency parameter was not used.

Conclusions:

A solution for the compression of images of computed tompgraphies of patients using neural networks has been presented.

Even though the backpropagation network is thought to establish a correspondence between input and output, this work presents a clear application of the use of the hidden layer.

Unlike conventional compression methods, this algorithm does not use redundant pixels directly as a key point of the compression, but the results to be obtained greately depend on the training patterns used. [HEL][GON][BAX]

Due to the nature of neural networks this algorithm can be directly parallelized: since neurons of a same layer work independently from each other a parallel architecture can be thus easily implemented.

Although out of the scope of this work, it is possible to use pattern representations to work on colour images. In this case, an increase of training time produced by the increase in size of the neural network, and the application of a larger set of training patterns than the one used here for gray levels, would have to be considered.

All documentation is available at the L.I.D.I., Laboratorio de Investigación y Desarrollo en Informática (Laboratory of Research and Development in Computer Sciences), 50 y 115 1er. Piso, La Plata.

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