Constitution of the Medical Image Compressed Using Support Vectors

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Abstract: *This paper deals constitution of compressed image after learning by support vector machines applied to microscopic images. The compression is used to reduce medical image size defined by an important acquisition for each exam, so, big size for storage and a lot of time for transmission. The compression ratio is satisfactory, but the result image is different from the original image because the compressed image has only support vectors, so we have loss of visual information.*

Keywords: compression, kernel function, medical image, support vector machines.

1. Introduction

The human eye doesn't perceive all details of image despite the human eye retains for some time, printed image on the retina.

The medical image represents a bigger size according to acquisition tool. For example, the image obtained by microscopy requires one mega octet and if we multiply this size by the number of cuts made for each exam, storage volume will be large [1].

Consequently, the only solution to reduce storage space and transmission time is medical image compression to achieve it.

A lot of work we're interested by compression using statistical methods or machine learning methods [2].

The compression or information theory amounts to Claude Shannon since 1948 allowing returning message the shortest possible, essential for comprehension or without redundancy [3].

In this paper, we propose the Support Vector Machines (SVM) or the separators wide margin for their performance [4] in machine learning applied to image compression.

2. Image compression

The image compression is applied to reduce image size lossless important information keeping an acceptable visual aspect.

There are two types of compression, lossless compression and lossy compression.

Lossy compression allows removing redundant information. It's possible to have the same image, but the data was removed and can't be recovered. The losses are undetectable to the eye, but the initial image is not identical to the decompressed image [5].

However, lossless compression does not eliminate any information. It's possible to find all pixels of the original image. So, after decompression, the reconstituted image is identical to the initial image [5].

In this work, we will test a method to see if it can be used as lossless or lossy but preferably it is no loss because we are dealing with medical images where loss of information can change the diagnosis.

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3. Support Vector Machine

Support Vector Machines are a method for supervised learning suggested by Vladimir Vapnik in 1992. This supervised technique results from statistical theory [6].

The goal of SVM is to find a linear classifier to separate data and maximize distance between classes. This classifier is called a hyper plane.

The closest points, that are used to determinate the hyper plane, are called support vectors. So, it is being on the margin.

The principal idea of binary SVM is to trace data on the space of higher dimension by using kernel functions for identifying the hyper plane which maximal margin to separate training examples.

Kernel function used in these experimentations is polynomial function and radial function:

$$k(x, y) = (x.y + 1)^d \tag{1}$$

$$k(x, y) = \exp\left((x - y)2 / \sigma^2\right) \tag{2}$$

We can say that only the examples corresponding to the support vectors are really useful in learning [7].

So, the support vectors resume important aspects of the data set. We can, so, compress the examples set retaining only the support vectors.

For our project, we used multi-class method One-Vs-Rest (OVR).

OVR is the simplest method of multi-class SVM or K binary SVM classifiers are built: one positive class against all negative classes. The decision function chooses the maximum value of K binary decision.

4. Results

4.1. Configuration

The images used are a type « astrocytoma » of “II” grade; it is of central nervous system tumors, of which growth is slow on different categories according to principal localization [8].

We used C++ Builder 6 for the pre-treatment of medical images to have the RGB value (Red, Green, and Blue) as entry data of SVM-Light Multi-class [9] for supervised learning.

4.2. Pre-treatment

We take pictures of different size; each image is divided by blocks of 16 x 16 pixels. In each block, we regroup the same pixels which have the same value RGB in the same class for each image. Then after, we start to learn each bloc with SVM-Light Multi-class [10] because it is easier to learn by block than to learn an image.

The result of the learning give us the support vectors [10], these points are used in image compression because it's the representative points in the image.

4.3. Experiments

For image compression, we must go through these steps (see Fig. 1).

The parameter selected for polynomial function “equation (1)” is the parameter which have minimized learning error and which have maximized classification ratio as presented in support vector machines for classification [4]. So, the polynomial degree (d) value is 3 and the radial gamma (σ) value is also 3.

We choose for our experimentation three cases. In all cases, the image is reconstituted by line using support vectors [10] generated by learning.

The compression ratio is calculated using image size saved on disk with this equation:

$$\text{Compression ratio} = \frac{\text{compressed image size}}{\text{sample image size}} * 100 \tag{3}$$

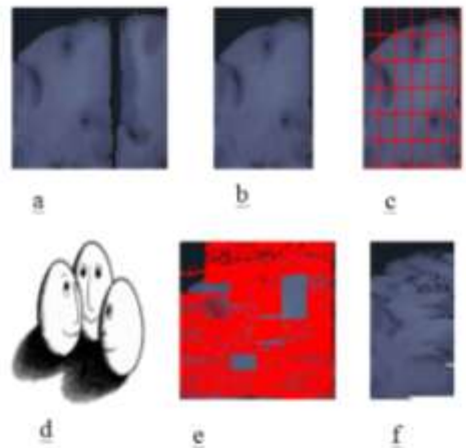

Fig. 1: Experimentation steps: a) Original image; b) Sample image; c) Blocks image; d) SVM Learning; e) SVs Image; f) Compressed Image.

Case 1

The image sample used is Astrocytoma with frontal section of 98x98 pixels. The image size is 28.3 Ko. The size of the compressed image is 21.1 Ko, so, the compression ratio calculated with the polynomial function is equal to 74.55 %. The size of the compressed image with the radial function is 0.43 Ko, so, the compression ratio calculated is equal to 1.51 %.

Fig**.** 2**.** Sample image in case 1.

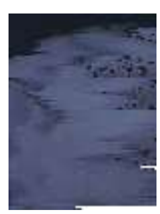

Fig**.** 3**.** Compressed image with polynomial function in case 1.

Fig**.** 4**.** Compressed image with radial function in case 1.

Case 2

The image sample used is Astrocytoma with a frontal section of 230 x 230 pixels in image. The image size is 155 KB. The size of the compressed image is 106 KB. The compression ratio calculated for the image with the polynomial function is equal to 68.38%. The size of the compressed image is 0.95 KB. The compression ratio calculated for the image with the radial function is equal to 0.61%.

Fig. 5. Sample image in case 2.

Fig. 6. Compressed image in case 2 with polynomial function.

Fig. 7. Compressed image in case 2 with radial function.

4.4. Discussion

We notice that:

- The compression ratio is better in the two cases compared to result found with images different texture [11].
- The compressed image is different from sample image because we lost a lot of pixels which are not support vectors.
- Two images having different size give the same compression ratio such as case 1 and case 2 for small image and average image.
- When we compare between the polynomial kernel and radial kernel, we can say that radial function gives a better compression ratio compared to polynomial function but point of view visualization, we lose a lot of information with radial function.

TABLE I: Comparison Between Compression Ratios in the Two Cases.

Case	Sample size	Kernel	Compressed size	Compression rate
Case 1	28,3 KB	Polynomial	21,1 KB	74,55%
		radial	0,43 KB	1,51%
Case 2	155 KB	Polynomial	106 KB	63,38%
		radial	0,95 KB	0,61%

5. Conclusion

In general, we can say that the proposed approach achieves good results of compression ratio. So, it allows reducing the amount of redundant data in medical images. Compression is crucial and requires time to reduce the size of an image with high computing power, even hours [10]. Also, for these reason that compression tools are reserved for authors of the applications. But the decompression step will be reserved to the end user that needs to be fast and it's our prospects.

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