Content Adaptive Compression of Images Using Neural Maps

Udo Seiffert
Leibniz Institute of Plant Genetics and Crop Plant Research
Gatersleben, Germany
seiffert@ipk-gatersleben.de

Abstract - *High-Throughput Screening (HTS) in biomedical environment is often based on image acquisition and processing. In many of these cases the images are characterised by two properties – (i) they are in great quantities and high resolution, and (ii) they contain limited and similar matter. The first property leads to an enormous demand of storage capacity making* ***any*** *image compression appropriate, while the second one paves the way for* ***content adaptive*** *image compression. However, this requires an easily adaptable and reliable image content selection method. By means of Neural Maps this paper demonstrates how unsupervised clustering can handle this.*

Key words - content adaptive image compression, unsupervised clustering, Self-Organizing Map, Neural Gas

1 Introduction

The usefulness of image compression to save either storage resources when keeping them or communication bandwidth when transmitting them is generally acknowledged and needs not to be further motivated. As long as a lossless method (see Sect. 2) is applied, the image content remains completely unchanged after decompression. Otherwise a trade-off between high compression ratio and low image degradation has to be found.
While in case of image compression for transmission purposes a sophisticated and thus possibly quite time consuming method seems not appropriate, in case of storing, particularly when storing means rather archiving, some considerations on the compression method promise much more benefit. Here, the compression time does not play such an important role, since the image compression might subsequently follow the image acquisition which often takes quite a few moments.
Due to its large-scale image data sets often containing high resolution images, particularly biomedical High-Throughput Screening (HTS)[1] [11] does not only request image compression at all, it also offers interesting and very promising environments for *content adaptive* image compression. This is caused by the fact, that the images are often rather similar to each other in terms of

[1]Neither the general approach of content adaptive image compression nor the specific considerations within this paper concerning image content selection with SOMs are limited to biomedical applications. Each other environment being characterised by the mentioned properties may benefit from these techniques as well.

- **Origin and device specific transfer functions of image acquisition equipment.** This makes the images technically homogeneous. Technically caused distortions and artefacts are generally less image dependent and can be indirectly incorporated in the compression.
- **Limited number of contained objects.** The images contain objects or structures which are always the same or at least very similar, e.g. the same type of cells or cell tissue. Furthermore, often only specific objects or structures are subject to further processing or human inspection. Only these image areas must be restored in high quality after compression, while all others may be more degraded.
- **Limited occupation of the colour space.** The images are often in a particular color shade. This makes a full colour space aware compression not necessary. One or more color planes (real or virtual ones) can be limited in their bandwidth or even completely left out.

All these properties allow to benefit from the advantages of prospective *content adaptive* image compression as a more tailored and thus more effective alternative to still quite common – non content adaptive – image compression methods.

2 Image compression revisited

In general, image compression algorithms are commonly associated with one or more particular file formats and are supposed to be versatile and fast. There are several standard image file formats (see Tab. 1) available, offering a big variety of internal compression algorithms [14]. While RLE and LZW based compression [22] is originally lossless, JPEG [15] is a lossy compression format causing an adjustable degradation of the compressed / decompressed image. It still offers a reasonable and finely adjustable balance of retained quality and gained compression. The newer JPEG2000 [20] can be both lossy and lossless (nearly lossless) and outperforms JPEG and many other methods. For further details in the context of the application of these standard methods to biomedical images refer to [18].
Depending on a particular application or task many of the mentioned file based compression methods have their strengthes. On the side of lossless compression *tif* and *png* are rather popular, while *jpeg* is the most frequently applied lossy compression method. A quite comprehensive survey of the performance of these methods in biomedical High-Throughput Screening can also be found in [18].
Unfortunately a number of compression algorithms, which are scientifically interesting, very well performing, and even versatilely applicable, could not prevail as a (commercial) file format. Thus, in addition to the above mentioned standard methods, there are a number of non file based algorithms, like for example EZW (Embedded image coding using Zerotrees of Wavelet coefficients) [19], SPIHT (Set Partitioning in Hierarchical Trees) [16] and LMSE (Least Mean Square Encoding) [5] or LOCO-I (LOw complexity, COntext-based) [23] and CALIC (Content-based, Adaptive, Lossless Image Coding) [24], which even adapt themselves to the image using context-based predictors. Since these algorithms are often not available in standard image processing software, they are not used very frequently.
Since almost all of these methods are driven by a predefined algorithm in the sense of how the images are transformed from the original domain to a destination domain, a different

Table 1: Selection of standard file formats and corresponding compression schemes as well as their suitability for storing image data in a High Throughput Screening environment. From [18].

File format	Compression algorithm	Max. color depth	HTS suitability
Bitmap (*bmp*)	None	3×8 bit	–
	Run Length Encoder (*RLE*)	3×8 bit	+
Graphics Interchange Format (*gif*)	Lempel-Ziv Welch (*LZW*)	1×8 bit	– . . . – –
Joint Pictures Expert Group (*jpg*) or (*jpeg*)	Discrete Cosine Transformation (*DCT*)	3×8 bit	–
JPEG2000 (*jp2*)	Discrete Wavelet Transformation	3×8 bit	+
		3×16 bit	++
Portable Network Graphics (*png*)	ZLib	3×16 bit	++
Tagged Image File Format (*tif*) or (*tiff*)	None	3×16 bit	–
	Lempel-Ziv Welch (*LZW*)	3×16 bit	++

approach suggests itself to find an *optimal* form or definition of a transformation, maybe at a given compression ratio, by an adaptable system – for example an Artificial Neural Network (ANN). Early work dates back to the late 1980ies / early 1990ies [6, 4, 21, 1]. A detailed description of neural network based image compression with feed-forward nets can be found in [18].

However, since even in this case all parts of a single image or even all images of a set are treated by the same compressor, that of course has been adapted to the considered image or image set as a whole, nevertheless these methods are only scantily content adaptive. In order to achieve a more pervasive content adaptation, an in [17] suggested and in [18] refined system can be utilised (see also Fig. 1). Each image to be compressed is divided into image blocks. All blocks are analysed regarding to their content considering all aspects mentioned on the list in the introduction. This image content selection leads to a number of classes. Only image blocks belonging to a particular class are used to optimize the corresponding compressor. This way each compressor develops into an 'expert' for a specific and, depending on the number of classes, more or less limited image content.

Obviously, the classification, controlling the image content selection, sets the main properties of the entire system. These issues, being the focal part of this paper, are going to be discussed in the next section.

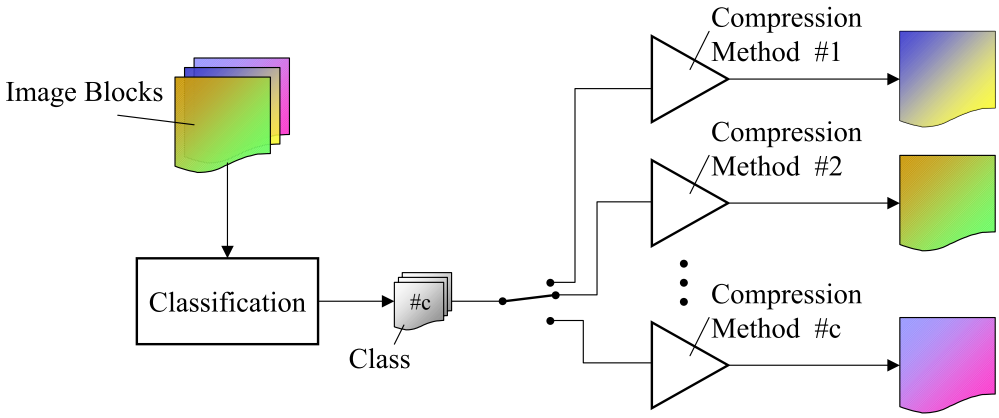

Figure 1: Based on image blocks a classification by means of extracted image block properties (i.e. similarities on image level) is performed. Depending on the detected class, each block is assigned to and processed by a specialized 'expert' compression method. This method may be but must not necessarily be neural network based as well. From [18].

3 Image content selection

3.1 Self-Organizing Maps

The image content selection as crucial part of the entire image adaptive compression system is to be evaluated in relation to the most prominent parameter controlling each compression system – the compression ratio. Generally, there are two ways: either it is a-priory fixed by the user or it is kept flexible and dynamically set within the system. This leads to the following scheme.

***Adaptive* compression ratio by . . .**

Complexity measure. If the image decomposition is done based on a complexity measure, the compression ratio has not to be specified in advance. This is only a putative advantage, since often in the absence of other now necessary parameters a user ends up at a pre-defined compression ratio. The complexity measure may be based on entropy, object-background separation, texture analysis, or other. It must be derived from image features. Although there is no standard definition, usually image complexity is defined as some ratio of background homogeneity and foreground clutter [7]. In practical implementation this leads to some serious problems to find suitable image features, which describe its complexity with regard to a *compression relevant* complexity. Furthermore, this is numerically very extensive and it seems to be questionable whether an extensive feature extraction, just to obtain a complexity measure, is a sensible method in this context.

Variable image decomposition. This generally possible method in fact is even more problematical. In extension of the above mentioned method, which assumed a fixed block size, any complexity measure is used to find an optimal size of the image blocks. As an advantage, these blocks have not to be analyzed furthermore, because a complexity measure has already indirectly been applied. However, if the block size is not fixed, it seems to be very hard to manage the succeeding compressors.

***Fixed* compression ratio by . . .**

Similarity adaptive compression. This seems to be the most straightforward and at the same time most promising approach. After all, a pre-defined compression ratio seems very intuitive for the user. The classification is based on similarities on image level. This is exactly that criterion intended to develop and distinguish the class corresponding 'expert' compressors. Thus it is a very native one. Generally, the whole spectrum of unsupervised classification algorithms is available.

A Self-Organizing Map (SOM) can be used to perform this similarity based classification [12]. For that purpose the SOM is unsupervised trained with a number of typical images. After this training, some classes[2] are formed, which now can be used to pass the image blocks to the corresponding compressor.

3.2 Growing SOM to respect different complexity

The above mentioned considerations regarding an adaptive compression ratio are in fact directed to respect different complexity of the processed image data set currently used to set up the compression system. Since, among others, the number of classes, and thus of different compressors, controls the final overall restoration quality, an adaptive number of classes seems to be very promising. For that purpose the standard SOM has been substituted with a growing variant according to [8].
This method provides an adaptive growing of an initially small map (here $2x3$ neurons) by stepwise insertion of rows or columns of neurons. The weights of the new neurons are interpolated from their previously trained neighbours. Each insertion step alternates with a regular training of the map of the current size. The growing is stopped after the change of the results drops below a given threshold.

3.3 Alternative variants

Although the (growing) SOM works very well (see Results section), it might be interesting to investigate some alternatives. The SOM itself offered some principle directions, e.g. to implement a different similarity measure [10] to redefine the base of the class formation. Because this is a rather wide scope, it has not yet been tested in this context.
Since the compressors run independently of each other, a relationship among the classes in the image domain is not necessary. Thus the SOM inherent property of topology preservation is not required, not even used. This opens up the field for unsupervised clustering without topology preservation. Implemented and tested paradigms are Neural Gas (NG) [13] and, according to the previous subsection, its size adaptive variant Growing Neural Gas (GNG) [9]. Other unsupervised neural architectures, i.e. Adaptive Resonance Theory (ART) [3, 2], are suitable as well. Its advantage is the inherent growing feature.
A comparison of the properties of these alternatives is given in the next section.

[2] For a concrete number of classes at a given image data set see Tab. 2

Table 2: Results of 5 different unsupervised neural networks as image content selection method for a fixed compression rate. A data set containing about 500 screening images ($2.600x2.060$ pixels) from a biological investigation [18] has been used. The data set is available on request from the author. The compression ratio is kept fixed to 0.125. The given range of the reconstruction error corresponds to 10 repetitions of the compressor network training. A comparative study with standard methods can be found in [18] as well.

Network type	Number of classes	Reconstruction error (RMS)
SOM [12]	9	$9 \cdot 10^{-4} \ldots 3 \cdot 10^{-3}$
Growing SOM [8]	8	$6 \cdot 10^{-4} \ldots 1 \cdot 10^{-3}$
NG [13]	12	$1 \cdot 10^{-3} \ldots 4 \cdot 10^{-3}$
Growing NG [9]	14	$1 \cdot 10^{-3} \ldots 3 \cdot 10^{-3}$
ART [3, 2]	5	$2 \cdot 10^{-3} \ldots 4 \cdot 10^{-3}$

4 Results

In [18] a comprehensive documentation of different compressors is given. In this paper the focus is on the image content selection as a necessary pre-processing within an image adaptive compression method. As compressor base-technique Multiple-Layer Perceptrons with hidden layers being 8 times smaller (compression ratio 0.125) than the input / output layers of 64 ($8x8$ pixels block size) have been used. The number of classes for the used image data set varied between 5 and 14 according to the used content selection method.

As to be seen in Tab. 2, the values of the reconstruction error have a rather high variance for the same network type. However, the variance between the different networks is not much higher. The number of classes is quite steady, although there are significant differences between various network types. This is of course depending on some parameters controlling the network training, particularly in case of the growing variants and ART.

Numerical details and computation speed issues are not further considered. Generally, the growing variants tend to be slightly slower. Of course, this also strongly depends on the actually used implementation. Insofar, a detailed and comprehensible comparison is very hard to obtain.

Generally, the SOM / Growing SOM show the best results. Although the Neural Gas family leads to more classes, which might imply a better reconstruction error, its results are not better. On the other hand, the ART alternative is not as worse as the relatively low number of classes may one let suspect.

An analysis has shown that the differences between the single content selection methods are not statistically significant, due to the relatively high variance of the compression networks.

5 Conclusions

This paper demonstrated the properties of a content adaptive image compression method by means of a number of unsupervised clustering techniques used to select the image block content to direct all blocks to an 'expert' compressor. Each of them is adapted to a rather limited variability of input data, which makes it very effective. All investigated clustering techniques have been applied to a biomedical image data set containing similar matter.

Investigations into a variable image compression rate led to discontenting results, especially regarding the handling of the entire compression system. However, this should be bearable, since the user can conceptually specify any desired compression rate in advance.
In case of a fixed compression rate the results demonstrate that several clustering techniques, ranging from standard Self-Organizing Maps up to Adaptive Resonance Theory networks, solve the image content selection task. There are slight advantages for the Growing SOM having less classes and thus less compressors but still a good reconstruction quality at a given fixed compression rate.

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