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CONTRIBUTIONS TO THE DIGITAL MEDICAL IMAGINES COMPRESSION
PhD thesis - Summary
To obtain the scientific title of doctor at
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The thesis is structured on 7 chapters and one annex.

Chapter 1, entitled **Introduction**, introduces the motivation that led the start of the research presented in the thesis. It also outlines the objectives research and the articles which were confirmed and which were resulted from the undertaken research.

In the last decade, computers evolution and information technology has led to a major leap in imaging in general and in medical imaging in particular. Due to this rapid development, new medical investigative techniques were created, that could not have existed in the absence of powerful computing equipment, for example the Nuclear Magnetic Resonance (MRI) and Computed Tomography (CT) procedures. All these has led medical field to grow faster from 8.75% in 2015 to 9.1% in 2016, as mentioned in the "2016 Global Medical Trend Rates" report published by Aon Hewit Insurance and Risk Management [2]. An important contribution to this development has had it, and it is expected to have it, medical imaging.

The large number of medical imaging equipment has resulted in increasing the amount of data which needed to be saved over long periods of time. This is due to the fact that the multitude of medical imaging equipment generates a multitude of images that have the most diverse formats and dimensions. The formats in question are generally those required by the manufacturer of the medical equipment concerned, which they consider appropriate for the investigation type.

The investments in this area are considerable [1]. For example, USA spent in 2015 over 18036.65 billion dollars. As a result, in 2012 the amount of digital medical information, which was 500 pentabytes, is expected to reach 25,000 pentabates in 2020 [1]. It is shown in [3] - Big Data Analytics for Healthcare, that in 2015 two pentabots (665 terabytes) of digital data were generated per hospital; 80% were computer tomography images and radiographs respectively. Every year the amount of medical imaging data increasion is between 20% - 30%, higher than in the previous year.

This PhD thesis proposes a new image format for digital images representation for general case, and in particular for medical image resulting from an medical imaging investigation. The method is based on the Local Binary Pattern (LBP) concept introduced by Ojala T and Pietikäinen M. [4, 5], an operator that allows describing the image texture by the mean an integer variable variable vector. The proposed image format is called **L**ocal **B**inary Pattern **C**ompressed (LBC).

In Chapter 2, entitled **Image Formats used in medical imaging**, a synthesis of the most used imaging formats is made. Each type of image is analyzed from the point of view of how a picture is quantified by the medical equipment; it shows the image accuracy and the average of image format size used. The synthesis is followed by another analysis of the most used medical imaging platforms, focusing on the most widely used platform, called DICOM.

There is currently a wide variety of medical imaging techniques that are used depending on the medical investigation nature. What is worth noting is that the used techniques have closely followed the technological imaging developments.

The first imaging investigation method that has been used has used X-rays. Subsequently, it has largely been replaced by ultrasound-based ultrasound technology.

New methods for generating medical images have emerged together with the information technology development. Thus, a computerized CT scan that uses targeted X-rays, can create 3D images of the human body's interior. Thereafter, Nuclear Magnetic Resonance (MRI), based on the fact that the human body has more than 70% water, has the potential to excite hydrogen protons under the influence of magnetic field and consequently to receive the signal to modify their state. The provided signal depends on the humas tissue nature, enabling the computer to be interpreted and reproducing with great precision all types of tissues of the human body.

A digital image is any image that comes from a scanner, a digital camera or a computer. The images stored in a computer are "digitized," they have undergone a process that transforms a real-world image into numerical data (digital values) made up of rows and columns. This digital image organization can be described as a pixel matrix. A pixel (PICture ELement) is the smallest element from a digital image and has three numerical / digital attributes: color, opacity, and matrix position (given by two plane coordinates). The information is stored in the computer in 0 and 1 binary format.

Computers are used for storing and manipulating numbers, so once the image has been digitized, it can be used to preview, archive, modify, display, transmit or print the image in a variety of ways.

In Chapter 3, entitled **Local Binary Pattern Operator** the LBP operator is analyzed. In this analysis is presented the basic variant of this method, as well as the variants that have developed over time. The analysis was aimed at determining the LBP variant that can be used to define the proposed image format in the thesis.

The Local Binary Pattern was first described in 1996 by T. Ojala, M. Pietikäinen and D. Harwood, [4]. Since then, this operator has proven to be a powerful tool in analyzing image textures and has been used so far in Machine Learning for grading and extracting features that involve images.

The local Binary Pattern (LBP) operator is based on the fact that the texture comprises two complementary elements: a model – a pattern - and its power [4, 5]. The operator can apply to both grayscale and color images. In this analysism the techniques that are applied to a grayscale image will discussed. For color images, the LBP operator's principle usage is the same, with the observation that it applies separately for each RGB color plane of the image.

Since 1996, when the first Local Binary Pattern was proposed, many variants have been explored by the literature due to its performance and ease of use. Article [25] proposes a further reduction of keys number taken into account for the purposes of classifying images. The authors have succeeded in reducing the space to 36 codes from the 59 codes of the uniform models, which are obtained by using a radius 1 circular region and the number of neighbors equal to 8.

The Local Binary Pattern operator is one of the tools that has improved the quality and performance of image compression / decompression, plus a statistical and structural method to improve image texture analysis.

One of the many benefits this operator has is that topologies can be changed by our application to get the best results. The methods, presented so far, use the LBP operator for static image analysis.

In Chapter 4 is entitled **Static image compression using the Local Binary Pattern operator**. The LBC format is proposed as a new image format. The proposal starts from a picture acquired by imaging equipment (regardless its nature - camera, scanner or medical imaging equipment) which is saved in a two-component format. The first component is a average values image and the second one a "dispersion" image. The "dispersion" image is obtained using the LBP operator in the classical version where a 3x3 pixel region is considered. The two images are saved in a new format, called LBC (Local Binary Pattern Compressed). The LBC format, that contains the two images, is 4 times smaller than the original image. To determine the LBC format quality, a metric quality metric SSIM (the acronym of the Structural Similarity Index Metric) was used.

The proposed technique has two aspects. A first aspect is that the application leads to an image format different from what is currently available. The second is related to the fact that it has a mechanism for compressing, respectively decompressing the pixel's matrix that defines the original image. Combining the two components, in the context of using two complementary images, leads to a better format especially for large images.

As described in a previous chapter, the Local Binary Pattern (LBP) technique allows describing the image texture by means of a vector that may vary in size, depending on the LBP variant used. In the classic version, LBP describes a 3x3 area of image texture through a single pixel.

Basically, this pixel defines the pixel variation on the LBP boundary relative to the center pixel. Counting the obtained values from the whole image analysis, which takes into account all the values obtained in this way, a vector with a dimension of 256 values that uniquely defines the image from which it originated is obtained.

Digital images lose their accuracy during transmission, compression, processing or storage, which can lead to a degradation of their visual quality. For cases where images are finally being analyzed by a person, quality assessment is important. The alternative is to use an objective method to estimate the perceived image quality.

In order to get the greatest possible compression, so of a better LBC format, it was necessary to use a of comparing method of the two images (initial and reconstituted) to estimate the image quality format used - LBC, respectively.

The most commonly used algorithm for quality assessment is the Structural Similarity Index Metric (SSIM) presented in the 2004 article: Image Quality Assessment: From Error Visibility to Structural Similarity by Wang. The most common methods previously used were Peak Signal-to-Noise Ratio (PSNR) and Root-Mean-Square Deviation (RMSD). The popularity of these methods has fallen because it does not take into account the perceptual difference between two images.

Starting from building an LBP value, I propose to describe a grayscale image through two much smaller image sizes:

- The first image is based on the 3x3 size areas values that are entering in the LBP value process. This image is seen as an average pixel value that defines the image texture.

- The second image is the LBP values obtained from the basic version of this technique. This set of values represents the ratio (the pixel has a higher or lower value) in which the border pixels from the 3x3 zone are located relative to the central pixel. This is the reason, this image is seen as a pixels "dispersion" on the border relative to the center pixel. It is necessary to clarify this second image, namely: it is not a pure mathematical dispersion of this concept. This dispersion defines if the pixel's value around the average value is less than or equal to the pixels's average value. When reconstructing the image is needed to use a Gaussian or uniform distribution law that is altered by the values from the dispersion image.

The two image sets represent the compressed image from the image they come from.

Therefore, the format in which the image is retained is defined by two complementary images:
A. An average and
B. A "dispersion" image.

This new image format is called LBC image format, the acronym from Local Binary Pattern Compressed.

In Chapter 5, entitled **Experimental Results**, a study is conducted to determine the settings used by the LBC format. These settings refer to the dispersion ranges determination used to restore the original image during the LBC format viewing process. Two distribution laws were considered: uniform and Gaussian respectively. The experiments in which both grayscale and color images were taken into account, medical images generated by the imaging equiptment were taken into account. To determine the quality of the LBC format obtained in the context of this study, the SSIM metric was used.

During the tests, to determine the correlation between the compression index and the image size, the link between the image size and the compression factor was determined. The test was performed for each image set (medical images, color block images, very large or very small images but with many details). The compression step value considered is 1 and the maximum value, at which the compression step changes, is 1% from the calculated LBP value. These values were chosen because the intention was to determine the relationship between the image size and the compression factor.The results are presented in the following figures for each data set.

• For the data set containing echographic images, the compression index is between 2.715 and 3.557.
• For the data set containing images with colored blocks, the compression index is between 2.177 and 3.237.
• For the data set containing building images, the compression index is between 3.607 and 4.477.
• For the butterfly image set, the compression index varies between 3.388 and 4.143.

The calculation for the entire images set has been recalculated without taking into account the image nature. The following conclusions can be drawn regarding the link between image size and how the compression index changes:

(A) The compression index value is dependent on the image size. A larger image leads to a higher compression index.
(B) The relationship between these two sizes is not linear. Variations may occur due to the following factors:

- A dominant color is present in the image. The color type will increase or decrease the compression index, affecting the dependence between image size and compression factor;

- Image complexity. This is seen as color variations given in the image context, from one pixel to another (the image texture is rusty). Large variations will decrease the compression index.

The following set of experiments pursued two objectives:

I. Determining the relationship between the compression index and the image size;

II. Obtaining the Gaussian constant and uniform values that determine the dispersion range size around the LBP value, to obtain the best SSIM similarity index.

In the context of these experiments, a set of 20 images representing different classes of images (ultrasounds, colored blocks, buildings - very large images but with many details, butterflies - very small pictures but with many details) were used. These classes have been chosen due to the texture's diversity and colors present in the images, in order to have the largest possible range to define the surrounding diversity, as accurately as possible. The following conclusions were reached:

- Images compression is dependent on the information nature presented. The image texture will influence the compression process, which requires determining the criteria how this process takes place. These criteria will refer to the determination of the best technique for generating pixels around the LBP average (Gaussian or Uniform distribution); determining the most appropriate constants that determine the dispersion range size around the LBP.
- Regardless the nature's information presented in the image (given by its grayscale or color tones), a good SSIM similarity index can be obtained between the original image and the reconstructed image. This index may be within [0.7-1].
- The value range, for the previously specified SSIM similarity index, can be obtained for a percent constant value that is used for the LBP dispersion range using a value that is within [0.1-2%] from the average LBP value.

In Chapter 6, entitled **Compression of Static Medical Digital Images. Experimental results**, a study was conducted on the effectiveness of using the LBC format for medical image generated by various imaging equipments. These images are distinguished from ordinary (photographic) images by their size, resolution and last but not least by the content. The study was performed for ultrasound and radiography images that were taken from medical reference databases in the field. The LBC format for medical images has been confirmed by the study. It has also been shown the usefulness of this format for large-scale medical image.

The study aimed to determine the indexes performance related to the image compression technique. Tests that have been performed have only considered medical images, due to the fact that the proposed compression technique addresses, in particular, this image category. The performance shows that the compression factor and the similarity index, which are directly influenced by the exact Gaussian constant and uniformity determination, can determine the dispersion range size around the LBP and distribution law to be used in image reconstruction (uniform or Gaussian). It has also been studied whether the compression process is influenced by the original medical image format (BMP, JPG, PNG).

The study led to the following conclusions:

- The maximum performance for the performance indices (compression factor, SSIM similarity index) is obtained if the value 1 is used for the constant determining the LBP dispersion range size.

- It was determined that the best law, that can be used to reconstruct pixel values, is the uniform one. Between the use of the uniform distribution law and the Gaussian distribution law for pixel reconstruction, studies have shown that there are small differences with a higher quality (compression factor, SSIM similarity index) between the two laws in case the uniform distribution law.

- Studies have shown that the original image type that is compressed (the most commonly used medical image formats - BMP, JPG, PNG) do not significantly affect the compression process. However, it can be seen that BMP or PNG images lead to a higher compression factor, with a decrease in the insignificant similarity index.

Chapter 7, entitled **Conclusions and Personal Contributions**, presents the conclusions resulting from the LBC format use. These conclusions refer to the proposed format used for representing both general and medical images.

The researches, done for this thesis, aimed to define a new image format. This format is suitable for medical image resulting from a patient's image process. This direction is important to be developed and pursued, as it is currently generating extremely large amounts of medical images. All these images must be saved for medical purpose, to have a picture of a person's medical history. The new format attempts to solve two issues raised by medical imaging, namely:

A. The images size are larger on the one hand and on the other hand the large number of images that are obtained during a single medical investigation. As a result, the image format must have a compression component that reduces its size, when the image is storedon the disk.

B. The second issue concerns the need to ensure a good medical image quality that ensures the correctness of the medical act when the image is interpreted.

The following objectives have been achieved:

1. These features analysis of the currently used image formats have been performed. This analysis sought to define the features that are common for the existing images formats. The analysis has also expanded on how they are used by the medical imaging.
2. A synthesis of the Local Binary Pattern concept was seen as a image texture descriptor, which can embody structural information that uniquely defines the image. This synthesis aimed to determine the LBP variant that can be used to define a new image format.
3. The study was carried out, whose purpose was to find a way to build a robust image format that would lead to a high compression factor in the context of preserving its content as accurately as possible.
4. After determining the building's technique for the proposed image format, to study the image format quality also became necessary. The study purpose was to finalize the formatting criteria definition according to the context in which it is used.

The research results, which was carried out over the five stages, was finalized by proposing a new image format called **LBC** (the acronym of **L**ocal **B**inary Pattern **C**ompressed).

The method involves describing the image to be stored through two complementary images:

I. An average value image resulting from the 3x3 pixel LBP central pixel retention that is used for image analysis.

ii. A "dispersion" image representing the LBP value resulting from the LBP type calculation.

The image format, resulting from this process (compression type), results in the synthesis information which characterize the image. This information is used to reconstruct the image in a rebuilding process; two image pixel generation methods can be used to restore the image. In the first method a uniform distribution law was used to generate the image's values; the second methos is a Gaussian distribution law. The distribution laws parameters are defined by the two complementary images that define the compressed image.

In order to show this method's viability for representation, a study in Chapter 5 was conducted in the thesis. Viability consisted of comparing the original image, existing in various JPEG, GIF, BMP and other formats with LBC image format. For comparison, a similarity index is now used, called SSIM, which shows how similar two images are in terms of texture, contrast and luminance. These experiments pursued two objectives:

- Determining the link between the compression index and the image size;
- Obtaining the value of the Gaussian and Uniform constants that determine the dispersion range size around the LBP to obtain the best SSIM similarity index.

In these experiments context, images from medical databases used for the imaging investigations calibration were used (*The American Institute of Ultrasound in Medicine, A digital library of radiology education resources, Medscape [49, 50 , 51]*). The following conclusions resulted:

- Images compression is dependent on the information nature present. The image texture will influence the compression process, which requires determining the criteria for how this process takes place. These criteria refer to the determination of the most appropriate technique for generating pixels around the LBP average (Uniform or Gaussian distribution), like determining the most appropriate constant that determines the dispersion range size around the LBP.
- Regardless of the information nature present in the image (given by its grayscale or color tones), a good SSIM similarity index can be obtained between the original image and the reconstructed image. This index may range from [0.7 to 1].
- The values range in which the previously specified SSIM similarity index appears can be obtained for a percentage constant value that is used for the LBP dispersion range using a value that is in the range of [0.1-2%] of average LBP.

In the study conducted in Chapter 6, experiments of the proposed format were performed, which only considered medical medical images, because the proposed compression technique addresses this category of images in particular. The performance indices that were considered refer to the compression factor and the similarity index, which are directly influenced by the exact Gaussian and Uniform constants determination, which determines the size of the dispersion range around the LBP and distribution law , To be used in image reconstruction (uniform or Gaussian). It has also been studied whether the compression process is influenced by the original medical image format (BMP, JPG, PNG).

The study led to the following conclusions:

- The maximum performance for the performance indices set (compression factor, SSIM similarity index) is obtained if used for the constant, which determines the LBP dispersion interval size, the value 1.
- It was determined that the best law that can be used to reconstruct pixel values is the uniform one. Between the use of a uniform distribution law and a Gaussian distribution law for the reconstruction of pixels, studies have shown that there are small differences between the two laws with a higher quality (compression factor, SSIM similarity index) for the uniform distribution law case.
- Studies have shown that the original image type that is compressed (the most commonly used medical image formats - BMP, JPG, PNG) do not significantly influence the compression process. It is found that BMP and PNG images lead to a higher compression factor with a decrease in the insignificant similarity index.

The contributions for this thesis refer to:

1. Theoretically defining a new, original image format, which was called LBC (**L**ocal **B**inary **C**ompressed).

2. Making a synthesis in which the imaging formats currently used in imaging in general and in medical imaging in particular, have been analyzed.

3. Make a LBP operator review and its usage variants. Following this synthesis, a LBP variant was defined to construct the optimal LBC image format.

4. An application that builds the proposed LBC image format. The application was used in experiments to determine the functional characteristics of the developed format.

5. There were two studies categories in which the LBC format behaved:

   A. The first studies set was designed to determine the optimal LBC format settings. The determined settings ensure optimal LBC image format performance, in the general case of an image that has a classic format (JPEG, BMP, PNG), regardless the imaging technique that resulted from it.

   B. The second studies was designed to determine the appropriateness of using the format in medical imaging.

The two studies results have led to the conclusion that the proposed format can be used to represent medical images, providing a considerable image compression up to 4 times and given a similarity with the original medical image over 96%. For these reasons, the proposed image format may lead to a considerable reduction of the image storage space in general and medical images in particular.

The results obtained were validated by publishing 4 articles, of which two are ISI indexed, and two IEEEs.

In the present research, a series of papers have been presented and published which follow and reflect the various stages of research that have been undertaken. These works are:

1) Ildikó-Angelica SZÖKE, Vasile STOICU-TIVADAR, Diana LUNGEANU. Sleep fragmentation. A study on how daily activites affect out sleeping, *Intelligent Engineering Systems (INES)*, 2015 IEEE 19th International Conference on 3 – 5 Sept 2015; Pages: 259-263, DOI: 10.1109/INES.2015.7329718
Indexată ISI

2) Radu Andrei ŞTEFAN, Ildikó-Angelica SZÖKE, Ştefan HOLBAN. Hierarchical clustering techniques and classification applied in Content Based Image Retrieval (CBIR), *Applied Computational Intelligence and Informatics (SACI)*, 2015 IEEE 10th Jubilee International Symposium on 21-23 May 2015; Pages: 147-52, DOI: 10.1109/SACI.2015.7208188
Indexată IEEE

3) Ildikó-Angelica SZÖKE, Diana LUNGEANU, Stefan HOLBAN. Image compression techniques using Local Binary Pattern, *Applied Machine Intelligence and Informatics (SAMI)*, 2015 IEEE 13th International Symposium on 22-24 January 2015; Pages 139-143, DOI: 10.1109/SAMI.2015.7061863
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4) Ildikó-Angelica SZÖKE, Vasile STOICU-TIVADAR, Diana LUNGEANU. A comparative study of using the LBC format for compressing medical images. *IEEE 15th International Symposium on Applied Machine Intelligence and Informatics (SAMI 2017)*, January 26-28 2017 in Herl'any, Slovakia
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