Application of the Laplacian Pyramid Decomposition to the Enhancement of Digital Dental Radiographic Images for the Automatic Person Identification

Dariusz Frejlichowski and Robert Wanat

West Pomeranian University of Technology, Szczecin,
Faculty of Computer Science and Information Technology,
Zolnierska 49, 71-210, Szczecin, Poland
{dfrejlichowski,rwanat}@wi.zut.edu.pl

Abstract. The paper provides some experimental results on medical images enhancement, namely digital dental radiographic images of entire dentition — pantomograms. This problem is a first step in the process of automatic identification of persons basing on the mentioned kind of images. The most crucial task is the emphasizing of some characteristics, e.g. shapes of the teeth and dental fillings. These features are widely used as an input for the methods of automatic dental identification. In the paper the Laplacian pyramid-based image enhancement approach is utilized. This method has been successfully used for other radiographic images — mammograms and computed tomograms (CTs). Exemplary methods of uniform and non-uniform Laplacian pyramid enhancement are presented along with their influence on a typical image.

1 Introduction

Digital radiography has become increasingly popular in the last two decades over its analog counterpart. The usage of computers and electronic detectors in lieu of film speeds up the process of developing photographs, removes the necessity of using possibly harmful chemicals and allows for further image processing. The latter reason is especially significant, since X-ray examination is considered intrusive and allowed only in certain time intervals. Therefore, the ability to increase the legibility of a low-quality image provides an extended margin of error for radiography technicians and in the end, helps the physician (in the described case — a dentist) in making a correct diagnosis. Every commercial dental software program allows, to some degree, for image enhancement. Some popular programs have been described in [1] by Lehmann et al., along with the list of the methods implemented by them. According to the authors all the programs offer contrast and brightness adjustments, scarcely including image filtering and comparison options.

There have been previous attempts at improving the quality of radiograms in general. Most of them focus on decomposing the source image into layers containing a subset of the information derived from the original image. Afterwards,

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the layers can be processed independently allowing for an improvement of different types of signals — both high- and low-frequency. There are two major approaches to the decomposition of original images. The first one is based on the wavelet transform and the second — on the Laplacian pyramid.

In wavelet-based decomposition, continuous wavelets are used as the basis functions. The restriction of continuity must be upheld in order to prevent discontinuities in the resulting image, thus rendering the popular Haar transform inutile. Wavelet-based approach has been tested in [2] and [3]. Its main drawback, as discussed in [3], is the appearance of ringing artifacts during the reconstruction of the image.

In Laplacian pyramid decomposition, the images are firstly low-pass filtered using a Gaussian filter and downsampled and the achieved result is interpolated to the original size and subtracted from the original image at the end. The result becomes the next layer of the pyramid and the subsampled intermediate image becomes the original image in the next step of the algorithm. This process is reiterated until the image size reaches one pixel. This method is more robust than the wavelet-based one and it will be described more precisely in the following sections. We focus in the paper on the Laplacian-based decomposition and its usefulness in enhancement of dental radiographs.

The described process of enhancement has to be performed in order to improve the quality of the pantomograms before they can be further used in the process of automatic human identification, as described by Jain in [4]. Even though the image enhancement is frequently mentioned as the first step of the human identification process, specific methods used are scarcely mentioned. Zhou and Abdel-Mottaleb ([5]) proposed a rather simple method of using top-hat filtered and bottom-hat filtered versions of the original image in the process of enhancement ([5]):

$$X_E = X_O + X_T - X_B, \tag{1}$$

where:
X_O — the original image,
X_E — the resultant enhanced image,
X_T — top-hat filtered version of the image X_O,
X_B — bottom-hat filtered version of the image X_O.

This approach is sufficient for bitewing images used in the study presented in [5], but proves inefficient when only pantomograms are used for identification.

Pantomograms require relatively low amounts of radiation, taking into consideration the surface that is presented on the radiogram. Therefore, they are considered to be of lower quality than the other two popular types of dental radiographic images: bitewing and periapical. Some additional image enhancement, such as edge sharpening and contrast improvement, is highly recommended and could prove beneficial at the later stages of the process, i.e. image segmentation and feature extraction.

Dental fillings and teeth shapes are two major sources of information used by identification methods based on dental radiograms and any improvement in their legibility will be sought for the most, but amelioration in other aspects, such as trabecular structure visibility, will also be described. An exemplary image being an object of interest in the paper is provided in Fig. 1.

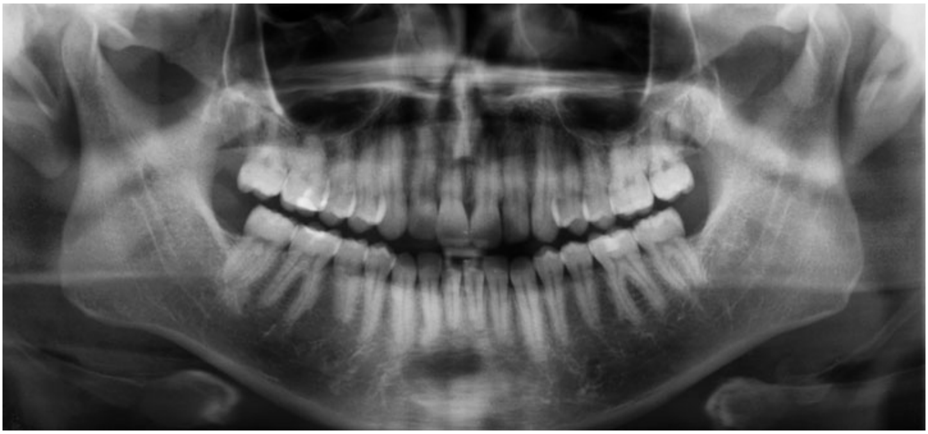

Fig. 1. Sample digital dental radiographic image, used courtesy of Pomeranian Medical University

2 Image Quality Enhancement

The concept of Laplacian decomposition of an image was firstly introduced by P. J. Burt and E. H. Adelson in [6]. Subsequent layers of Laplacian pyramid are calculated by subtracting consequent layers of a Gaussian pyramid. The process can be described using the equation ([6]):

$$\begin{aligned} X_k &= \downarrow (\bar{X}_{k-1}), \\ L_k &= X_{k-1} - \uparrow (X_k), \end{aligned} \tag{2}$$

where:
$\downarrow (X)$ and $\uparrow (X)$ represent the process of downsampling and upsampling the image by a factor of 2,
$\bar{X}_k$ — low-pass filtered image X_k (with X_0 denoting the original image)
L_k — the successive layer of the Laplacian pyramid.

Gaussian filter is popularly used as a low-pass filter, but Stahl et al. ([7]) point out that small binomial filter kernels can also be used.

The above decomposition method was later used as a basis for multiscale image enhancement in [4], [7] and [8]. The methods used there were uniform, i.e. applying the same transformation to all the layers, with a small change in the method presented in [8], where the gain parameter could vary depending on the layer. Those methods will be examined later in this paper, after presenting the non-uniform methods, where the layers are processed independently.

Before we describe existing methods of enhancing the quality of a decomposed image, it must be noted that there is no simple quality measure of an image. Whether an image is considered of high or low quality can only be measured by its ability to satisfy some specific needs. Because these needs can be different, as dental radiographs could be used by a dentist as well as a forensic specialist identifying a body, we assumed that a measure of quality is a subjective prediction of how the enhancement could affect further stages of digital image processing, e.g. image segmentation. This measure does not necessarily overlap with the definition of quality agreed upon by experienced physicians, for whom some important minutiae might have been lost in the process of enhancement.

As it was noted, the images that form the Laplacian pyramid contain progressively lower frequencies of the image data. In result the first layer of the pyramid can be instinctively identified with the trabecular structures of the mandible and maxilla. Some of the smaller layers of the pyramid contain unobstructed contours of the teeth and surrounding bones and on the lowest level there is only the mean of the image brightness. Stahl et al. ([8]) noted that because of the downsampling performed after the frequency range is reduced, even though every layer theoretically represents the spatial frequencies of up to half the Nyquist frequency of the previous one, the spatial frequencies contained in the actual layer are on a par with the frequencies of the previous layers. An example of the normalized 4th layer of the sample image is presented in Fig. 2.

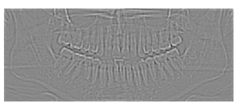

Fig. 2. The 4th layer of the Laplacian pyramid decomposition achieved for a pantomogram. The image is eight times smaller than the original one and contains lower frequency signals — edges.

The simplest modification of the processed image can be achieved by changing the value of the only pixel on the last layer of the pyramid, thus changing the bias of the original image or relative brightness. Operating on the layers with low frequency data — usually the 2-3 layers before the last one — allows for easy enhancement of large portions of the original image. This can be especially useful if the image is not evenly developed due to a non-uniform distribution of radiation when the radiograph was taken — a simple averaging filter or even substitution of all coefficients on the layer with the mean value of that layer solves this problem.

Additional enhancement of an image can be achieved by using the unsharp filter on a layer containing high frequency signal, ideally the second or third layer. The first layer contains too much fine detail, including noise, therefore the usage of the unsharp filter on it would give a similar result as using it on the original image. When using it on further layers the sharp edges of teeth and bone structures are enhanced without strong amplification of the noise.

The most significant drawback of the non-uniform methods is that they hardly work automatically. Images of the same type should have the same layer distribution, but it has to be determined beforehand, what could be time-consuming. Uniform layer manipulation methods are free of this problem.

The use of multiscale images in contrast enhancement was introduced in [9] and further developed in [7]. It is also commercially used in Agfa ADC system. Vuylsteke et al. proposed a contrast equalization function given by the formula ([7]):

$$f(x) = a(\frac{x}{|x|})|x|^p, \tag{3}$$

where ([7]): "x are normalized to the range $[-1, 1]$ and the factor a is needed for rescaling the resulting image to the original dynamic range". This operator resembles a standard exponential operator, working for both positive and negative pixel values.

This function is further developed in [8], where Stahl et al. proposed another version of equation 1, with slight modifications ([8]):

$$\begin{cases} r(x) = G \cdot x \cdot (1 - \frac{|x|}{M})^p + x, & if\ |x| \leq M \\ r(x) = x, & elsewhere \end{cases}, \tag{4}$$

where M is the upper limit for linear enhancement and G is a constant gain. This contrast equalization function was also used in [3]. Its main drawback is a significant amplification of image noise. Fortunately it can be easily solved — Stahl et al. proposed an additional method of noise suppression in their model, given by the formula ([8]):

$$S_n(x, y) = b(x, y) \cdot S_f(x, y) + (1 - b(x, y)) \cdot S_o(x, y), \tag{5}$$

where S_n is the final value of the pixel, $b(x, y)$ is the attenuation factor such that it is ([8]): "smaller than 1 in the noise sensitive region and equal to 1 elsewhere", S_o is the original pixel value in the layer being contrast-equalized and S_f is the pixel value after initial equalization.

3 Experimental Results

The various approaches to Laplacian pyramid manipulation, presented in the previous sections, were tested using several pantomograms. The effect of every method will be presented on the exemplary image and some additional images will be shown to demonstrate the effect of the selected best method on other examples.

The first presented example (see Fig. 3) is a result of using the averaging filtration on low-frequencies layers.

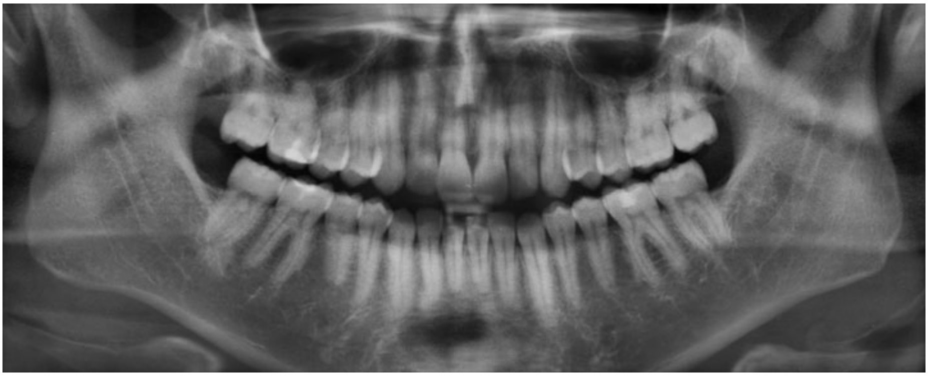

Fig. 3. The result of averaging the low-frequencies layers — smoother background and uniformly colored bones

The appearing discoloration in the general areas of cheeks and lower mandible has been removed and the background behind teeth has been smoothened. That could be helpful during the image segmentation, where smooth background and a uniform underlying bone color would improve the detection of edges belonging to crowns and roots.

The following example (see Fig. 4) shows the effect of using the unsharp filter on the second layer of the Laplacian pyramid decomposition.

Fig. 4. The result of the application of unsharp filter — the edges of teeth fillings and roots are improved

The all-important improvements can be seen in the areas that lacked sharpness in the original image — the surroundings of the roots, the fillings and the tips of the molars. Trabecular structures also look sharper and can be easily extracted from the image. The noise amplification is not as severe as it is the case of an unsharp filtering for the whole image. The contrast between the teeth and mandible\maxilla is rather low.

The effect of the contrast equalization function (for $p = 0.75$) on layers 3 through 11, achieved using eq. 3 for the sample image can be seen in Fig. 5.

Fig. 5. The result of the contrast equalization of a pantomogram — the edges of fillings, dental pulp and roots are more pronounced

The contrast of the most important areas has been significantly increased. Dark bone areas have become darker and bright teeth and the fillings have become brighter. This also causes the dental pulp to become more distinct, what can be valuable in diagnosing lesions in this part of the tooth. The silhouettes of the roots also have sharper edges, thus simplifying the separation of teeth from bone. Trabecular structure of the bones is also sharper than on the original image.

An example of the second contrast enhancing method, as described in equation [4], with the parameters $M = 0.15$ and $p = 1.5$, is presented in Fig. 6.

Fig. 6. Exemplary result of the contrast boost. It allows for an easier distinction between fillings and teeth and between teeth and surrounding bones.

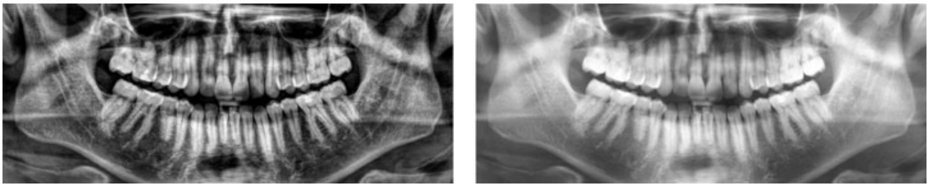

Fig. 7. The result of a combination of three enhancement methods (left) and the same enhancement applied to the image in spatial domain (right)

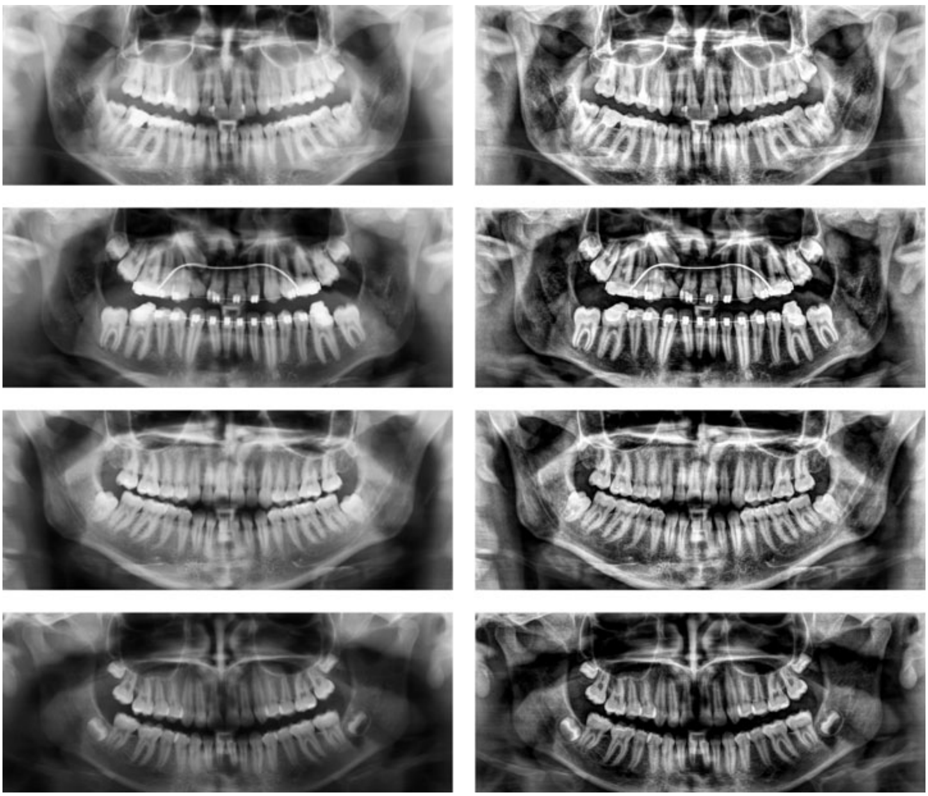

Fig. 8. The comparison between the original (left) and enhanced using the explored approach digital dental radiographic images (right). The enhanced images provide better basis for further image segmentation.

Considering further processing of the resultant image, this achieved image has the highest quality so far, with greatly improved contrast, sharper edges and the easier discernible difference between bone and teeth. Trabecular structures are also sharper than as a result of any method applied so far. The most important is the high contrast between three distinct groups of objects useful in people's identification: the teeth, surrounding bones and teeth fillings.

The last performed by us experiment was based on a combination of three operations on a digital dental radiographic image. We have used the following sequence: the averaging of the two layers next to last, unsharp filter on the second layer, and the second presented in the paper method of contrast enhancement, achieved using eq. 4. The result is provided in Fig. 7. As we can see some very interesting elements are emphasized, e.g. roots of the teeth. The same image was enhanced in spatial domain, using the above methods and is also presented in Fig. 7. The averaging could not be implemented in the spatial domain as it would remove all the details from the image, so a more complex operator would have to be included in order to remove the effects of the unequal exposure of the picture. The use of the unsharp filter used in spatial domain also increased the noise.

At the end of this section, we present some additional results of the explained approach, achieved using the combination of the three methods. The results, compared to the original images, can be seen in Fig. 8.

The images after the enhancement have generally better contrast, easily discernible teeth from surrounding bones and sharper edges. In all of the presented cases, the image enhancement improved the possibilities of successful teeth and fillings segmentation at the cost of amplified noise.

4 Conclusions

The approach presented in this paper covers only one group of existing radiogram enhancement methods. We did not compare methods that do not employ the Laplacian pyramid decomposition, like the mentioned wavelet-based image decomposition ([2,3]) or a method based on manipulation on local standard deviations ([10]). Moreover, the evaluation was purely subjective. However, the obtained enhanced images gave promising results seeing that the regions of an original image, where the contrast was improved the most, were the regions that are the most important in the process of human identification, whether done by a specialist or automatically. Further improvement could be easily achieved at the cost of the automation, which is crucial when the size of an average dental radiograms database is taken into account.

As it was stated in the paper, the quality of an image can only be measured by its ability to satisfy specific needs, thus making the influence of selected methods on the accuracy of a sample persons identification system based on pantomograms the only reliable measure of image quality change. Therefore our future work will be concentrated on experiments exploring this influence on a larger database of pantomograms in order to validate the initial results presented in the paper.

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