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Automatic Detection of Landmarks for Image Registration Applied to Bone Age Assessment

EMMA MUÑOZ-MORENO[1], RUBÉN CÁRDENES[2,3], RODRIGO DE LUIS-GARCÍA[1], MIGUEL ÁNGEL MARTÍN-FERNÁNDEZ[1], CARLOS ALBEROLA-LÓPEZ[1]
Laboratorio de Procesado de Imagen (LPI)[1],
University of Valladolid,
SPAIN
{} http://www.lpi.tel.uva.es
Center for Technology in Medicine (CTM)[2],
Dpt. of Telematics Engineering [3],
University of Las Palmas de Gran Canaria,
SPAIN
http://www.ctm.ulpgc.es

Abstract: - Bone age assessment is a medical procedure to diagnose bone diseases, specifically, growth pathologies. As of today, it is carried out by visual inspection which, needless to say, is a tedious and time consuming action. Automated methods to carry out such a task are therefore desirable. In this paper we take a step in this direction by proposing the automatic detection of a set of anatomical landmarks in positions of interest in radiographs. Such landmarks will then be used to carry out a registration procedure described elsewhere to eventually come up with a bone age estimation. The algorithm finds the landmarks by performing a rough segmentation to find the finger axes and then intensity profiles along the axes are analyzed to locate joints between finger bones.

Key-words: - Bone age assessment, Thin plate splines, Landmark-based registration, Landmark detection, Hand segmentation

1 Introduction

In pediatric radiology bone age is often assessed as a way to diagnose growth pathologies and other bone diseases. This procedure is carried out by visual inspection of an X-ray of the non-dominant patient hand (i.e., the left hand for right-sided patients and viceversa). Two different techniques have been reported. The first one, namely, the Greulich-Pyle (GP) method [1] is an atlas-driven method, and it is based on visually comparing the patient radiograph with a number of atlas patterns of representative images for each age. Bone age is assessed on the basis of the pattern which more accurately resembles the patient radiograph according to the physician perception. The second one, called Tanner-Whitehouse (TW) method [2], uses a detailed shape analysis of individual bones of interest, defining a set of evolution stages for each bone. Scores are derived from each bone stage and summed to compute the assessment. The former method is easier but quite dependent on the physician criterion, whereas the latter is more complex, but more objective [3]. Regardless of the method used, bone age assessment is a tedious and subjective task [4, 5]; for this reason, an engineering effort to automate this task —based on image processing techniques—, is fully justified. In this paper we will have in mind a registration-based technique to that end.

Registration is the determination of a geometrical transformation that maps one image into another, aligning objects in both images [6]. Recalling the two methods briefly described in the above paragraph, notice that the GP method could be considered as a registration process between a patient X-ray image and a set of prototype images from the atlas. On the other hand, the TW method requires identifying several regions of interest (ROIs) where scores are obtained. If we define these ROIs on a template image and register other X-rays (tar-

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get images) against it, the ROIs should be correctly identified in the patient X-ray. Therefore, we understand that hand X-ray registration could constitute the core of an automated bone age assessment system.

Among the registration techniques proposed in the literature, we will consider the landmark-based [6, 7]. They start from a point set (the landmarks) whose positions are defined in both images, so that we may know how to map the landmarks. For the remaining points of the image, the transformation can be obtained by interpolation, for instance, applying a Thin-Plate Splines (TPS) algorithm [8, 9].

In order to fully automate the procedure, anatomical landmarks must be automatically found. This is by no means a simple problem, due to the high variability between the bones at different growth stages. In this paper, we propose an algorithm for the detection of landmarks, using a cascade of image processing techniques. A TPS registration will be carried out from these landmarks. We are only considering points in fingers, so the registration will be successful on this area, but not in other hand regions. Notice, however, that as for bone age assessment ROIs are our focus of attention.

In the following section the landmarks to be found are defined, and the problem we are facing is more specified. Then, the proposed algorithm to find out the landmarks is described, as well as the set of filters applied. In section 4 we discuss the results obtained by applying our method on several hand X-rays. Finally, we show the conclusions from this work and we propose some future prospective actions.

2 Problem statement

As stated above, registration of hand radiographs can help radiologist assess the bone age. One group of registration techniques are landmark-based [6, 7], which draw small errors near the landmarks. The TW method defines ROIs over the finger tip and the inter-phalangeal area; so, following this method, we will identify anatomical landmarks to automatically locate the windows defined in the method. To put it in short, it is our purpose to automatically detect the landmarks shown in Fig.1.

One of the most challenging issues we have to face is the difference among bone structures at every age. This can be observed in Fig.2, where a hand from a

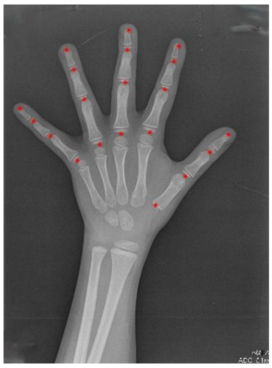
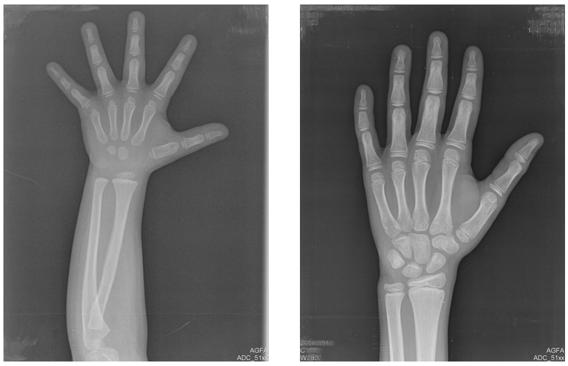


Fig. 1: Set of landmarks of interest.

very young patient (a) and other from an older one (b) are shown. In early ages the epiphyses (extremes of the large bones) are not present; as the growth takes place they appear separately from the bone and finally they fuse with the bone. In order to get correct and age-independent anatomical landmark identification these differences must be taken into account.

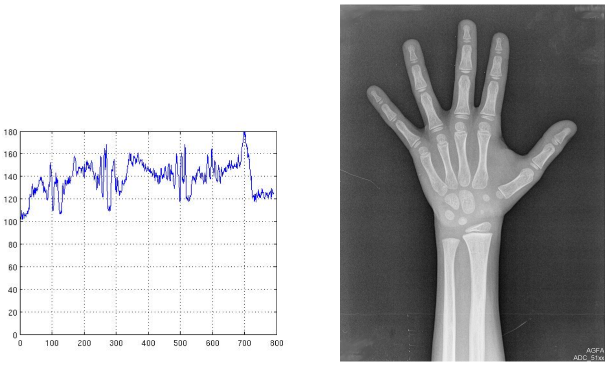


(a) (b)

Fig. 2: a) Hand X-ray from an early aged patient (carpal bones have not appeared, and epiphyses are small and separate from the bone); b)Hand X-ray from a higher aged patient (carpal bones are already presents, and epiphyses and large bones are starting to fuse).

Another problem we find is the difference in the pose of the hands in different images, as well as in the angle between the fingers. So, a general algorithm may be difficult to reach. Other reason that makes the landmarks detection not easy is the uneven intensity values according to the image area. To give an example, we show in Fig.3a the intensity profile along a finger axis.

Once we get the landmarks identified, we will apply the registration algorithm, namely, TPS, so that the ROIs are found in the target images.



(a) (b)

Fig. 3: a) Intensity profile along a finger axis; b) Example image for the landmark detection and registration.

3 Algorithm Description

In this section, we describe the steps taken to identify anatomical landmarks in a target X-ray image and to register it against a template one. The procedure applied will be illustrated on the hand shown in Fig.3b.

Firstly, noise is reduced by Gaussian filtering. Then, we extract bone edges in order to segment the structures of interest. In parallel, finger axes are extracted. The landmarks are finally detected from the segmented image and the finger axes. Once the landmarks are identified, we apply a TPS registration algorithm. A block diagram with the whole process is shown in Fig.4. In the following subsections, the algorithms used in every step are described in more detail.

3.1 Edge detection

In order to identify the bones of interest, we first extract the edges of the structures in the image. Edge detection is carried out by applying the Canny algorithm [10]. From the gradient of the image and its direction, it obtains the bones edges. In order to close the contour, Canny algorithm uses a hysteresis operator.

In the segmentation step, a closed contour is more important than a thin one. Therefore, we also apply an edge dilation to assure edges are closed lines. The result of this step is shown in Fig.5, where we can see the resulting edges, as well as the contour of other structures. Thus, this is a good image candidate to apply a watershed filter and segment the bones, as we describe in next section.

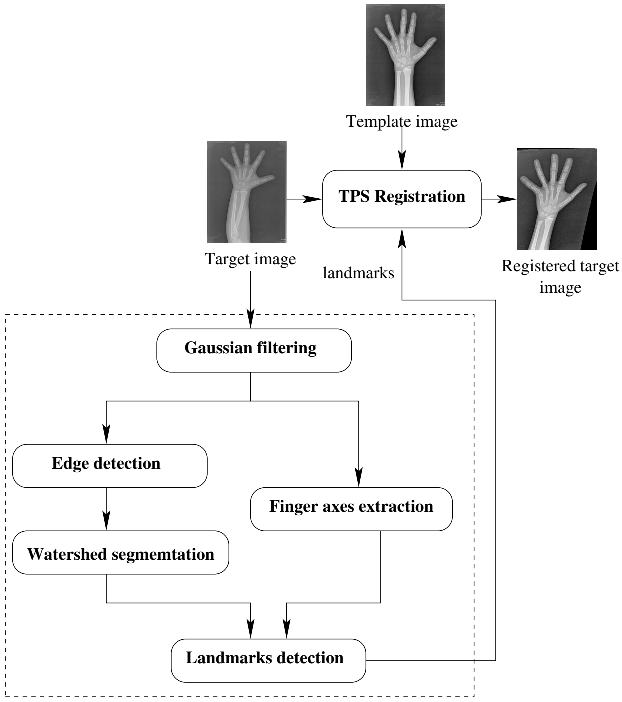


Fig. 4: Block diagram showing landmarks extraction and image registration.

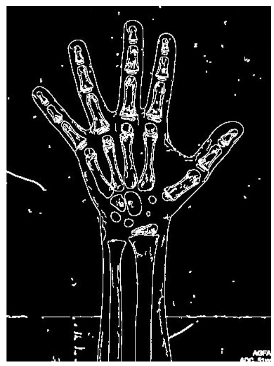
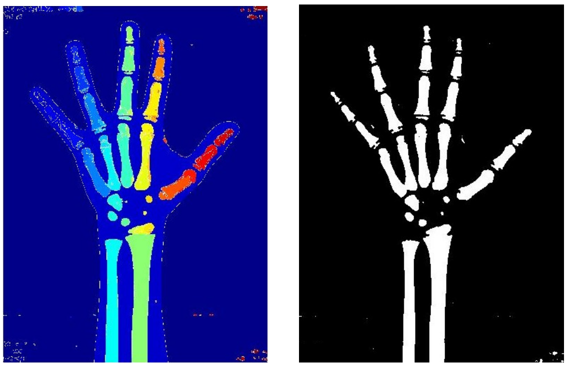


Fig. 5: Extracted contour

3.2 Segmentation

In order to segment the bones of interest, we apply a watershed algorithm [11] on the image we got from the previous step. The name of watershed is due to the fact of the image is considered as a flooded landscape. In this way, higher gray levels match with higher altitude and so on. By immersion of the image into the water, lower altitude regions will be first flooded. The lines where the water level from adjacent regions joints define the region border.

As result of the watershed filter we get a labeled image, as we can see in Fig.6a, where each color identifies a region label. Notice that there is a large number of regions. This over-segmentation is a problem of using watershed when a great amount



(a) (b)

Fig. 6: a) Watershed filtered image (each color represents a region); b)Segmented bone after thresholding the previous image.

of local minima appears. Since we only have to distinguish between two regions (bone and non-bone), we apply a junction criterion to the resulting regions. We consider as bone those regions whose areas are above a threshold. The threshold is defined as a proportion of the overall image area.

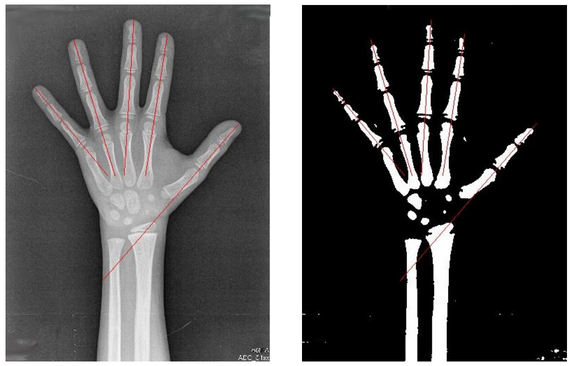
In Fig.6b, we show the binary image obtained; you can see that small regions in the background are considered as bone. This is not a problem for landmark detection because we will also take into account the finger axis, so the ROIs will be the segmented regions that are crossed by this axes. The way to extract the axes is explained in the next section.

3.3 Finger axes extraction

The determination of the finger axes is performed following the method proposed in [12]. Starting from the raw radiograph image, the background is removed by applying an adaptive threshold which varies with the position in the image according to local statistics. Next, a thinning algorithm is used to obtain a coarse skeleton of the hand. The branches corresponding to each finger form approximate longitudinal axes, but these need to the refined. This is done by approximating them by straight lines and repositioning them in the center of each finger by analyzing the successive cross-sections.

This procedure is appropriate for all fingers except for the thumb, since in this case the phalanges rarely appear completely centered in the finger (this can be seen in Fig.7).

The extension of the calculated axes is not suitable for the metacarpals, because they are not necessarily aligned with the phalanges. Therefore, a more complicated method has to be employed in this case, which produces points that are afterwards used for the determination of the thumb's axis (see [13] for details).



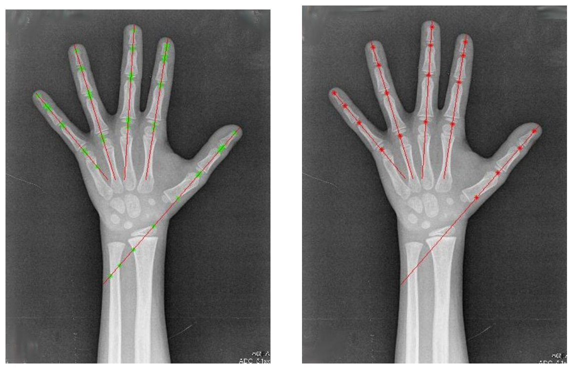
(a) (b)

Fig. 7: a) Finger axes over the original X-ray; b) Finger axes over the segmented image.

3.4 Landmarks Selection

At this point, we have the segmented image and the axes of the fingers. From these data, it is possible to determine the landmarks. For this purpose, we seek intensity changes in the segmented image along the straight lines that define the finger axes. These points, shown in Fig.8.a, allow us to identify the desired twenty landmarks.

First of all, we identify the end points in the distal phalanges as the first intensity change along the axis. The remaining landmarks are detected by computing the average point among nearby intensity changes. Therefore, the landmarks between phalanges are placed correctly disregarding the stage of development of the epiphysis.



(a) (b)

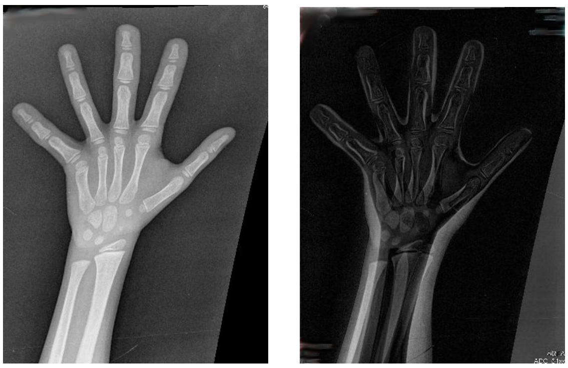
Fig. 8: a) Intensity change points along the finger axes; b) Landmarks detected in the example hand radiograph.

The resulting landmarks are shown in Fig.8.b. Here, the landmark at the inferior end of the thumb finger is not exactly adjusted, as a consequence of approximating this finger to a straight line. From these landmarks we can carry out the TPS registration, as explained in the following section.

3.5 Image registration

One kind of geometrical transformation used in landmark-based registration techniques are splines. They are elastic transformations that map a template image over a target one, according to some smoothing conditions. They start from the known correspondence between landmarks in the two images [7]. TPS is one particular class of splines, usually employed in registration, that can be understood as a bi-dimensional interpolation from a landmark set [6, 8].

The implementation of the TPS algorithm is reduced to solve a linear equation system to determine the transformation coefficients [9]. So, the registration procedure is efficient. The drawback of this method is that the error in areas far from these landmarks is higher than in the nearest areas since it only considers landmark information. However, by setting the landmarks in the region of interest we obtain a correct registration of these areas, as it is shown in Fig.9.a, where the example image is registered against the one shown in Fig.1. The error image obtained by subtracting both images is captured in 9.b.



(a) (b)

Fig. 9: a) Registered image from automatically detected landmarks; b) Registration error.

4 Experiments and results

The proposed method has been implemented in MATLAB and tested over a set of digital hand X-rays from patients in several bone ages.

Applying our method over a set of 40 images, the landmarks were correctly identified in 50% of them, and in 25% of the images all the landmarks except one. The overall percentage of landmarks successfully identified considering the whole set of images is 93,6%. In some cases, landmarks are not totally centered in each bone, since the axis approximate the whole finger with a straigth line. This effect is more frequent in the thumb, due to its curvature.

On the other hand, the method is less accurate in images from advanced aged patients. In this case, the bones are bigger and the gaps between them are so thin that the phalanges may not be separated by the segmentation step. In fact, 90% of the images where all the landmarks are not detected belong to this group of patients. Nonetheless, the success rate (landmarks correctly located respect to landmarks incorrectly located) in this kind of images is 87,2%.

5 Conclusions

In this paper we have applied different image processing techniques to automatically detect anatomical landmarks in hand radiographs. These landmarks allow us to register the images using the TPS algorithm. The final objective of the registration is the identification of the regions of interest used in the Tanner-Whitehouse method for the bone age assessment. Consequently the detected landmarks are placed in the aforesaid regions.

Automatic detection of landmarks is a challenging task due to several reasons. Firstly, the variability of the present structures among the different bone maturation stages. A second reason is the unequal hand poses in the images. And finally, the inhomogeneity of the intensity levels both inside the same image and among images. However, the performance of our algorithm has been tested over several images obtaining successful results. The parameters of the filters have been chosen empirically providing good behavior in most of the images.

As future work, we consider some research lines in order to improve our algorithm. First, we can consider these landmarks as a first approximation. Then, they can be displaced in a neighborhood according to some local criterion to a more accurate position. Other line consist in using a skeleton or medial axis of the fingers, instead of straight line approximations. This would result in more exactly centered landmarks in the finger bones.

However, let notice that it is not possible to assure exactly what is the *correct* location of the landmarks, due to the variability of the bones depending on the maturation stage. The final goodness of the algorithm would be better appreciated when included in an automatic bone age assessment. In this case, results obtained using the detected landmarks could be compared with the physicians measurements.

In the paper we have only considered the finger area. In order to identify all the windows considered by the TW method, we should extend the method to detect landmarks in other hand areas, namely, carpal, metacarpal, ulna and radius. Thus, this regions would be also correctly registered.

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