A NEW SEMI-AUTOMATIC APPROACH FOR X-RAY CERVICAL IMAGES SEGMENTATION USING ACTIVE SHAPE MODEL

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Abstract: This paper describes a new method for cervical vertebra segmentation in digitized X-ray images. We propose a segmentation approach based on Active Shape Model method whose main advantage is that it uses a statistical model. This model is created by training it with sample images on which the boundaries of the object of interest are annotated by an expert. The specialist knowledge is very useful in this context. This model represents the local statistics around each landmark. Our application allows the manipulation of a vertebra model. The results obtained are very promising.

1 INTRODUCTION

Nowadays, the radiography of the spinal column is one of the fastest and the cheapest way for a specialist to detect vertebral abnormalities. Furthermore, as far as the patient is concerned, this procedure has the advantage to be a safe and non-invasive. For these reasons, this exam is widely used and remains incontestable in the scope of treatments and/or urgent diagnoses. Despite these precious advantages, a meticulous and tiresome analysis is required by the practitioner. The nature of the radiographs is the origin of the problem. In fact, they are obtained by impressing the density of the tissues on a radiographic film. A bone is defined by a white color, a soft tissue by a gray level and an empty space by a black color. It is a fact that the images present low contrasts and some areas might be partially hidden by other organs of the human body. As a result, the vertebra edge is not always obvious to see or detect.

The problem of vertebra segmentation in digitized X-ray images is of great importance for the specialists. The extraction of quantitative data gives them a valuable computer-aided diagnosis.

There is a myriad of segmentation methods. Of course, they are not all recommended for the medical image processing and all the more so they don't all meet the difficulties concerning the X-ray images. The reader is lead to discover (Pham et al., 2000) for an overview of the current segmentation methods applied to medical imagery.

The vertebra segmentation has already been treated in various ways. The level set method is a numerical technique used for the evolution of curves and surfaces in a discrete domain (Sethian, 1999). The advantage is that the edge has not to be parameterized and the topology changes are automatically taken into account. Some works related to the vertebrae are presented in (Tan et al., 2006).

The active contour algorithm deforms and moves a contour submitted to internal and external energies (Kass et al., 1988). A special case, the Discrete Dynamic Contour Model (Lobregt and Viergever, 1995) has been applied to the vertebra segmentation in (Benjelloun and Mahmoudi, 2008). A survey on deformable models is done in (McInerney and Terzopoulos, 1996).

Other methods exist and without being exhaustive, let's just mention the generalized Hough transform (Tezmol et al., 2002), or the use of the polar signature (Mahmoudi and Benjelloun, 2008).

The difficulties resulting from the use of X-ray images force the segmentation methods to be as robust as possible. In this paper, we consider a technique based on the Active Shape Model (ASM) (Cootes et al., 1995). An active shape model is a statistic model designed from sample of images. This preconception regarding the shape to search in the image (a vertebra in our case) gives the method based on ASM an important robustness.

We will see that the effectiveness of the method highly depends on the initialization. The computer-

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aided diagnosis has to fulfill the same characteristic than the radiography technique, *i.e.* the simplicity and the rapidity. Therefore, it is crucial to automate and to provide the results in acceptable times. Extensive research related to this issue has been done in (Long and Thoma, 2000; Long and Thoma, 2001).

This paper is structured as follows. In section 2, we explain the principles of the active shape model approach and our proposed segmentation method using this approach. In section 3, the results of the segmentation on data sets of cervical images are commented. Finally, section 4 presents our conclusions.

2 METHOD OVERVIEW

In this paper, we propose a new segmentation approach based on the active shape model theory. The goal of this method is to identify vertebra edges from the cervical spinal X-ray images. An Active Shape Model is a statistical model that describes objects shape. Basically, an active shape model (ASM) (Cootes et al., 1994) is a statistical model generated from a set of training samples. A series of corresponding points, called landmark points, are identified on the boundary of the target object in each training image. Then the training samples are regarded as vectors and statistical parameters of the vector distributions are computed using principal component analysis. By changing the parameters, new shapes can be synthesized. After the ASM is trained, it can be used to locate objects in a new image. The contour extraction process using ASM is a process of synthesizing an optimal shape that is most similar to the shape in the image. The statistical difference between the synthesized shape and the original model can be calculated. By restricting the difference to small values, the deformation can be limited to an acceptable range. In the followed section briefly reviews the ASM segmentation scheme.

2.1 Active Shape Model Method

The ASM method is composed of 4 steps (Figure 1):

1. Learning: placing landmarks on the images in order to describe the vertebrae
2. Model Design: aligning all the marked shapes for the creation of the model
3. Initialization: the mean shape model is associated with the corners of the searched vertebrae. This step can be manual or semi-automatic
4. Segmentation: each point of the mean shape evolves so that its contour fits the edge of the vertebrae

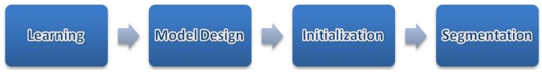


Figure 1: The steps of our framework.

2.1.1 Learning

A set of image samples has to be described by some landmarks. It is therefore common to choose as landmarks the corners of the vertebra and a reasonable number of equidistant points between these corners. Figure 2 shows an example of this process.

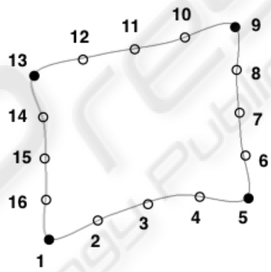


Figure 2: Vertebra marking.

Each shape in the set is represented by a vector x_i:

$$x_i = (x_{i1}, y_{i1}; x_{i2}, y_{i2}; \dots; x_{ik}, y_{ik}; \dots; x_{in}, y_{in})^T \tag{1}$$

2.1.2 Model Design

When the annotation phase is completed, it is necessary to align the shapes to make a correct statistical treatment since they are indeed positioned at various locations and orientations of an X-ray image. The algorithm is as follows:

1. Align each shape of the sample on the first one.
2. Repeat until convergence:
   (a) Compute the mean shape.
   (b) Adjust the mean shape to the first shape.
   (c) Align each shape on the mean shape.

Once the set of aligned shapes is available, the mean shape is calculated using the arithmetic mean of coordinates describing each element of the sample (see equation 2).

$$\bar{x} = \frac{1}{f} \sum_{i=1}^{f} x_i \tag{2}$$

A set of possible models is derived from this mean shape by the moving of points through specific directions called modes of variations. These directions are equivalent to the eigenvectors of the variance-covariance matrix of the sample. Finally, the model is described by the mean shape $\bar{x}$, the matrix P of the most significant eigenvectors p_i corresponding to the eigenvalues λ_i and a vector b of weight factors b_i. We have:

$$x = \bar{x} + Pb \quad (3)$$

With:

$$P = (p_1, p_2, \cdots, p_t)$$
$$b = (b_1, b_2, \cdots, b_t)^T$$

The equation 3 is used to decide if an object from an image can be considered as convenient. As the coordinates of the landmarks of an object are known and as the eigenvectors are unit vectors, it is possible to determine the vector b by the equation 4.

$$b = P^T(x - \bar{x}) \quad (4)$$

The values of the factors b_i allow to know if an object is convenient to the model. The values of b_i can vary in the following manner (Cootes et al., 1994):

$$-3\sqrt{\lambda_i} \leq b_i \leq 3\sqrt{\lambda_i} \quad (5)$$

2.1.3 Initialization

For the initialization process, we propose a semi-automatic process based on two points placed by the user on the left side of each vertebra on the superior and inferior corners. The mean shape is positioned according to this information.

2.1.4 Segmentation

Having generated a flexible shape model, we would like to find examples of the modeled form when it is present in the images. So, after the initialization step, shapes are fitted in an iterative manner, starting from the mean shape.

For each landmark belonging to the mean shape, it is necessary to analyze the surrounding texture. It is always important to consider changes in the level of gray in the same direction to ensure a coherent research. Therefore, it was chosen to analyze the texture around landmarks along the normal of the contour at that point (see Figure 3). Thus, a profile is defined as a vector containing the gradient of intensity for each point in the normal. Each landmark is moved to the direction perpendicular to the contour to n_s positions on either side, evaluating a total of $2n_s + 1$ positions. We can notice that these positions correspond to the profile of each landmark on the mean shape. In our experiments, we chose $n_s = 7$. The landmark is moved to the position with the lowest Mahalanobis distance (Cootes et al., 1995). After moving all the landmarks, the shape is fitted to the displaced points (by respecting the equation 5), yielding an updated segmentation.

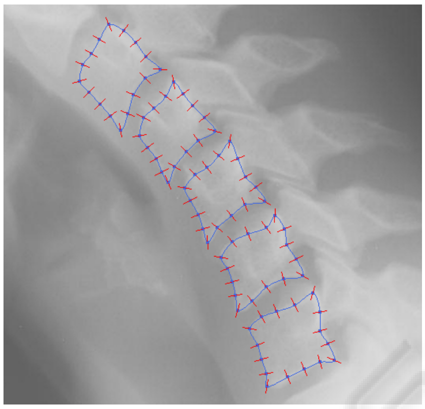


Figure 3: Normal of the contours for each point of the profile.

The search algorithm is given here:

Do:

- Search, along each normal of the shape, the best profile according to the computed mean shape. The new sections are landmarks and profiles found.
- Search shape model best suited to points found in the previous step. This will form the basis for the next iteration.

While the convergence condition is not met and the maximum number of iterations is not reached.

It remains to determine when to suspend the conduct of the search algorithm previously presented. The first condition of convergence proposed is to stop the search when all the landmarks remain fixed. However, it appears that this condition is too strict. We have therefore decided to stop searching when a small percentage of the landmarks continues to move. Specifically, we compare the shape obtained in the current iteration with all the forms built with previous iterations. For each of them, we compute the number of points that differ from those recently obtained. We then seek the minimum of these values. If the corresponding shape is close to the present shape, we then compare the number of points that differ between these two shapes. If the first value is less than 10% of the second, the convergence condition is met. To avoid an indefinite search if the vertebrae are not found, a maximum number of iterations can be fixed. If this number is reached, the search ends and the result of the current iteration is proposed as a final solution. In practice, when an initialization is done correctly, the method converge after 50 to 250 iterations.

3 EXPERIMENTAL RESULTS

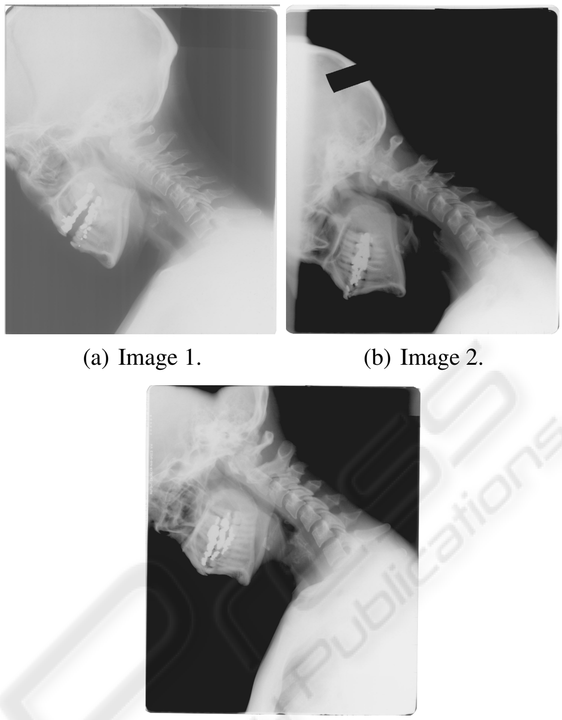
We proposed and developed a segmentation method based on the active shape model theory. Our goal was to produce a tool for vertebra detection in X-ray images corresponding to the cervical spinal column. We validated our method by using a test database composed of more than 10 000 X-ray images from the online database NHANES II of the National Library of Medicine (NLM,). Our application was developed in order to allow the use of a vertebra model. Figure 5 shows the segmentation results obtained by this kind of modelization.

We study in our experiments the influence of some parameters in the final segmentation result, such as the number of sample images, the profile structure and the number of landmarks by vertebra used to define the mean shape model.

For bothly a powerful and useful segmentation, the choice of images sample should be the task of a specialist. The dataset size recommended for the training set varies from one database to another. Nevertheless, the larger the sample, the best the built model. We proposed a sample composed of 25 images for our tests. This number provided good segmentation results. It is obvious that this number can be augmented, but by increasing the mean shape computing time.

By the same way, the number of landmarks has a direct influence on the quality of the segmentation results obtained by the search process. It is evident that the greater this number, the better the segmentation result. Nevertheless, it would be necessary to find a good compromise, in order to obtain a reasonable computing time for the search phase process. We carry out this compromise by using 20 landmarks for each vertebra.

The last parameter influencing the segmentation results is the structure of the profiles used for the search process phase. This one depends on two parameters: the number of points by profile and the distance between these points. We can also notice that to ensure an independence of this spacing with respect to the image size, this distance is proportional to the vertebra size. After various tests, we conclude that a profile of seven points spaced by a distance equal to 5% of the vertebra size is a good compromise. Figure 5 shows the segmentation results for the three images corresponding to the cervical spinal column (Figure 4) on the basis of the parameters presented above. After convergence, all the vertebrae are detected perfectly. The segmentation results for the chosen images tests show that vertebra edges are detected perfectly by applying the proposed segmentation approach, based on a vertebra model and using the Active Shape Model approach. The Table 1 proposes the vertebra recognition rate of our method on 50 images.



(a) Image 1. (b) Image 2.

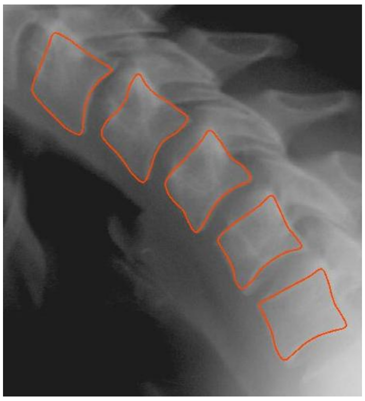
(c) Image 3.

Figure 4: Test images.

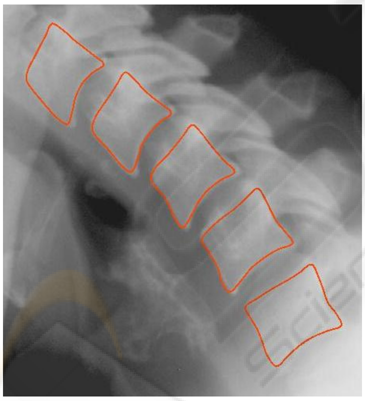
Table 1: Vertebra recognition rate.

Vertebra Type	Recognition Rate
C3	96%
C4	98%
C5	96%
C6	98%
C7	86%

(a) Image 1.



(b) Image 2.



(c) Image 3.

Figure 5: Segmentation results.

4 CONCLUSIONS

The goal of this paper was to present a semi-automatic technique applied to cervical vertebra edge detection in X-ray images. To this aim, we used a segmentation approach based on Active Shape Model. This method is composed of two stages: a stage of modeling and another of search. We proposed an approach which consists on modeling all the shapes of vertebrae by only one vertebra model. The multiple tests which we carried out on a large dataset composed of varied images prove the effectiveness of the suggested approach. We can also notice that the proposed method allows a fast contours extraction and is more reproducible than the manual method. This method can be adapted to other component of the spinal column: like dorsal or lumbar.

The principal inconvenient of this ASM based segmentation approach is the stage of training, which is time consuming. Another important problem of this approach is the impact of pose initialization in ASM: the closer the mean shape is placed to the actual object, the better the chances of having a successful segmentation are. In our case, we solve this problem by proposing a semi-automatic approach. So, we suggest to place the mean shape model on the image by using the vertebra left corners edges which are placed by the user. This approach produces a very good initialization of the search process.

In our future works we want to investigate a method aiming to propose an automatic approach of segmentation. To this end, we can use some corner detectors. We also consider the use of these segmentation results in order to analyze the mobility of the cervical spinal column. Another perspective of our work consists in using the *Graphics Processing Unit*: GPU, in order to accelerate the process of mean shape calculation, and also the ASM search stage.

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