Radiographs as Medical Documents: Automating Standard Measurements

Dov Dori[1], Adam I. Harris[2], Gustavo Gambach[1], Robert M. Haralick[3]
[1]Faculty of Industrial Engineering and Management
Technion, Israel Institute of Technology
Haifa 32000, Israel
[2]Rush Presbyterian St. Luke's Medical Center
Chicago, IL, USA
[3]University of Washington
Seattle, WA, USA

Abstract

Standard radiographs are documents that provide a significant amount of information for the orthopedic surgeon. From the radiographs, surgeons will make many measurements and assessments. A major problem is that measurements are performed by hand and most often by the operating surgeon who may not be completely objective. The evaluation of the spine radiographs includes progression of scoliosis (curvature of the spine), spondylolysthesis (malalignment of the spine), and progression of degenerative disc disease (such as a "slipped disc") or certain spine fractures.

While there are other factors that contribute to the variation from one radiograph to the next, there is an inherent imprecision in hand made measurements. To the extent that a computer could increase the accuracy and precision of these measurements, diagnostic accuracy would be increased, exposure to radiation would be decreased, therapies appropriately assigned. To alleviate the burden of manual measurements, which must be made by trained professionals, and make them more objective, we have initiated a program to automate certain radiographic measurements.

This work concentrates on the edge detection step. we present an edge detection model for standard radiographs, which will be the basis for the measurements step. In particular, we model the edges of interest as a linear combination of basis functions. The problem of edge detection is then presented as a supervised pattern recognition problem in which the parameters of the basis functions are learned during the training phase, and the recognition phase uses these learned parameters to locate pixels that belong to edges. Since edges may appear in any direction, we develop the mathematical tools to determine the gradient direction of the edge. Finally, we discuss future work in this project.

1 Introduction

Today, an orthopedic examination is rarely considered complete without radiographs. The orthopedic surgeon is therefore interpreting radiographs on a daily basis, and assigning treatments according to the interpretations. Part and parcel of the process of interpretation are measurements made on the radiographs. For example, the decision regarding the choice of brace treatment versus surgical treatment for scoliosis is based upon measurements on radiographs of the spine.

Certainly, no such decision is based entirely on measurements from the radiographs. However, the significance of these measurements is not limited to the initial evaluation. Every treatment, operative or non operative, has its risks and benefits. The medical community is obliged to review the results of the various treatments and, as the results dictate, revise the guidelines for treatment.

2 Edge detection techniques

Edge detection is the identification of the intensity changes corresponding to the underlying physical changes. To achieve radiograph understanding, computer systems must relate the raw input data to the physical structure that cause it, i.e., the objects being radiated. Edges are very likely to be projected as changes in the intensity data received by the sensor.

Over the last 20 years, several types of edges detectors have been developed.

A related operation, the "gradient," $|g(i,j) - g(i+1,j+1)| + |g(i,j+1) - g(i+1,j)|$ was proposed by Roberts [3]. It detects either a horizontal or vertical edge when $g(i,j)$ is the gray level at point (i,j). This operator involves only four points and is therefore extremely sensitive to noise and surface irregularities.

Hueckel's model [3] of an edge is a step function F in a circular disc. Hueckel's operator is an efficient solution to the minimization problem. The technique used is series expansion and truncation in the frequency domain. Specifically, the functions that are used as a basis are separable into a product of an angular and radial component, i.e. it applies Fourier analysis in polar coordinates.

More claims of optimality have been made by Marr and Pogio. The basic approach of Hildreth [8] is to convolve the image with a rotationally symmetric Laplacian of Gaussian and to locate zero crossings of the convolution. The Nevatia-Bavu [9] technique consists of determining the edge magnitude and direction by convolving the image with a number of masks and thinning and thresholding these edge magnitudes. Torre and Poggio [11] judiciously point out that better results may be obtained by using two directional filters with directional derivatives especially in the neighborhood of corners.

Haralick [4] locates edges at zero crossings of the second directional derivative in the direction of the gradient. Derivatives are computed by interpolation of the sampled intensity values. The occurrence of a digital step edge is detected if the zero crossings of the second directional derivative in the direction of the estimated gradient is negatively sloped. On some images, the resulting edges are visually better than the ones from the Marr-Hildreth detector.

Canny [2] defines certain desirable criteria for edge detection. He shows that in 1-D, the optimal filter is a linear combination of four exponentials well approximated by a first derivative of a Gaussian. In 2-D images, he proposes to use a combination of such filters with varying length, width and orientation . Shen and Castan [10] proposed a linear filter, in which images are convolved with the smoothing function $f(x) = -\frac{1}{2}\ln(b)b^{|x|}$ prior to differentiation.

3 A pattern-recognition approach to edge detection

Edges in radiographs present a more complicated problem than identifying a step function. Even applying the most advanced techniques still does not yield results that enable us to advance to the level of higher image understanding. We therefore propose here a basis for a model for detection of bone edges.

We model the edges of interest analytically as the linear combination of a number of basis functions $B_1(x_1), B_2(x_2), B_3(x_3)\ldots B_n(x_n)$ as follows.

$$I(x) = \sum_{i=1}^{n} b_i B_i(x_i) =$$

$$(b_1, b_2, b_3 \ldots b_n) \left\{ \begin{array}{c} B_1(x_1) \\ B_2(x_2) \\ \vdots \\ B_n(x_n) \end{array} \right\} = bB(x) \qquad (1)$$

The problem of edge detection is then presented as a supervised pattern recognition problem in which the parameters of the basis functions are learned during the training phase, and the recognition phase uses these learned parameters to locate pixels that belong to edges. Since edges may appear in any direction, in the next section we develop the mathematical tools to determine the gradient direction of the edge.

Figure 1 depicts the edge model in 3D space, where (r, c) is the image plane (rows and columns of pixels)

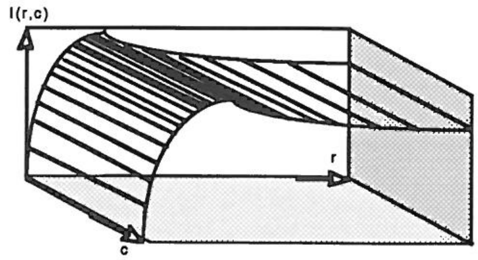

Figure 1: Radiation intensity through a schematic section of a bone

and the third dimension is the image intensity for each pixel. In figure 1, the edge is parallel to the c axis, therefore it can be modeled using equation 1 with $x = r$. Here, the gradient direction θ is zero.

However, either the normal curve in the wall of the vertebrae or curvature in the spine may result in an alteration in the orientation, making an angle θ with the r axis, as shown in Figure 2.

4 Determining the bone edge direction

By substituting $x = rcos(\theta) + csin(\theta)$ in equation 1 we generate a 3D surface that is a sweeping of the edge curve perpendicular to the gradient direction of θ.

$$I(r, c) = \sum_{i=1}^{n} b_i B_i(rcos(\theta) + csin(\theta)) \qquad (2)$$

The partial derivatives of I with respect to r and c are therefore:

$$\frac{\partial I(r,c)}{\partial r} = cos(\theta)\sum_{i=1}^{n} b_i B_i'(rcos(\theta) + csin(\theta)) \qquad (3)$$

and

$$\frac{\partial I(r,c)}{\partial c} = sin(\theta)\sum_{i=1}^{n} b_i B_i'(rcos(\theta) + csin(\theta)) \qquad (4)$$

A unit vector is:

$$\vec{g} = \frac{\left\{ \begin{array}{c} \frac{\partial I(r,c)}{\partial r} \\ \frac{\partial I(r,c)}{\partial c} \end{array} \right\}}{\sqrt{((\frac{\partial I(r,c)}{\partial r})^2 + (\frac{\partial I(r,c)}{\partial c})^2)}} = \left\{ \begin{array}{c} cos(\theta) \\ sin(\theta) \end{array} \right\} \qquad (5)$$

where the denominator was taken to be positive because the gradient direction is set to go upwards.

To estimate the edge direction, we assume that the neighborhood of a pixel can be approximated as a plane described in equation 6.

$$I(r, c) = \alpha r + \beta c + \gamma + \epsilon(r, c) \tag{6}$$

Here, $\epsilon(r, c)$ is the error function, the difference between the observed intensity values $I(r, c)$ and the expected ones, so we wish to minimize it. To this end, we convert equation 6 into a least-square problem:

$$\epsilon^2 = \sum_{r=-m}^{m} \sum_{c=-m}^{m} [I(r, c) - (\alpha r + \beta c + \gamma + \epsilon(r, c))]^2 \tag{7}$$

where $(-m, -m)$ and (m, m) are the coordinates of the lower left and upper right corners of the $(2m + 1) * (2m + 1)$ mask used as an approximation for the plane patch of the pixel under consideration, located at (0,0). We are looking for α, β and γ which minimize ϵ^2 . To find α that minimizes ϵ^2 we take the partial derivative of ϵ^2 with respect to α and equate it to zero.

$$\frac{\partial \epsilon^2}{\partial \alpha} = \sum_{r=-m}^{m} \sum_{c=-m}^{m} 2\,[I(r, c) - (\alpha r + \beta c + \gamma)]\,(-r) = 0 \tag{8}$$

Opening the parentheses in equation 8 we get:

$$-\sum_{r,c} I(r, c) r + \sum_{r,c} \alpha r^2 + \sum_{r,c} \beta r c + \sum_{r,c} \gamma r = 0 \tag{9}$$

where $\sum_{r,c}$ is shorthand notation for $\sum_{r=-m}^{m} \sum_{c=-m}^{m}$.

$f(r)$ is an odd function, because $f(r) = -f(-r)$. Since $f(r) = r$ is taken from $-m$ to m, it is a function taken over even limits (i.e., limits of the same size m).

γ^2 is an even function since it is constant. $\sum_{r,c} \gamma r$ is an odd function taken over even limits because it is a product of an odd and even function, both taken over even limits. Since the summation of an odd function taken over even limits is identically zero, $\sum_{r,c} \gamma r = 0$.

Equation 9 then can be written as follows:

$$\sum_{r,c} I(r, c) r = \sum_{r,c} \alpha r^2 + \sum_{r,c} \beta r c \tag{10}$$

The last term can be written as $\beta(\sum_{r=-m}^{m} r)(\sum_{c=-m}^{m} c)$ where both of the last two elements are identically zero.

Hence, we get:

$$\alpha = \frac{\sum_{r,c} I(r, c) r}{\sum_{r,c} r^2} \tag{11}$$

where the denominator is a fixed number $2(2m + 1)\sum_{k=1}^{m} k^2$ for a given m. For example, if $m = 2$, we have:

$$\alpha = \frac{3}{m(m + 1)(2m + 1)^2} \sum_{r=-m}^{m} \sum_{c=-m}^{m} I(r, c) r \tag{12}$$

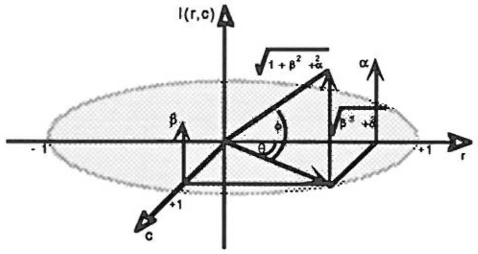

Figure 2: Inclination and gradient directions of unit vector

A similar development for β yields:

$$\beta = \frac{\sum_{r,c} I(r, c) c}{\sum_{r,c} c^2} \tag{13}$$

or

$$\beta = \frac{3}{m(m + 1)(2m + 1)^2} \sum_{r=-m}^{m} \sum_{c=-m}^{m} I(r, c) c \tag{14}$$

γ^2 is the elevation of the plane, therefore it may be taken as zero without loss of generality. To determine the relations between α, β, r, and c in the plane $f(r, c) = \alpha r + \beta c + \gamma$, we find (r, c) such that $r^2 + c^2 = 1$ (a unit vector) which maximizes $f(r, c)$. The direction of the vector will be the gradient direction, as depicted in figure 2.

Using Lagrange multipliers, we get:

$e(r, c) = \alpha r + \beta c + \gamma - \lambda(r^2 + c^2 - 1)$

$\frac{\partial e}{\partial r} = \alpha - 2r\lambda = 0 \Rightarrow r = \frac{\alpha}{2\lambda}$

$\frac{\partial e}{\partial c} = \beta - 2c\lambda = 0 \Rightarrow c = \frac{\beta}{2\lambda}$

$\frac{\partial e}{\partial \lambda} = r^2 + c^2 - 1 = 0$

Substituting r and c in $r^2 + c^2 = 1$, we get $(\frac{\alpha}{2\lambda})^2 + (\frac{\beta}{2\lambda})^2 = 1$ which yields

$\lambda = \frac{1}{2}\sqrt{\alpha^2 + \beta^2}$,

$r = \frac{\alpha}{\sqrt{\alpha^2+\beta^2}}$, and

$c = \frac{\beta}{\sqrt{\alpha^2+\beta^2}}$

Substituting r and c in the plane $f(r, c) = \alpha r + \beta c + \gamma$ and taking $\gamma = 0$ we get:

$\frac{\alpha^2}{\sqrt{\alpha^2+\beta^2}} + \frac{\beta^2}{\sqrt{\alpha^2+\beta^2}} = \sqrt{\alpha^2 + \beta^2}$

which is the amount we rise by taking a unit step in the gradient direction, as can be seen in figure 2. The actual way we traverse is $\sqrt{1 + \alpha^2 + \beta^2}$ and the gradient direction θ is found as:

$$\theta = \tan^{-1} \frac{\beta}{\alpha} = \tan^{-1} \frac{\sum_{r,c} I(r, c) c}{\sum_{r,c} I(r, c) r} \tag{15}$$

while the angle of the plane of inclination is:

$$\phi = \tan^{-1} \sqrt{\alpha^2 + \beta^2} =$$

$$\tan^{-1} \sqrt{(\sum_{r,c} I(r,c)r)^2 + (\sum_{r,c} I(r,c)c)^2} \qquad (16)$$

Having found θ, the adjustment of our edge model is done by using equation 2 rather than 1.

5 Modeling the edge detection as a supervised pattern recognition problems: future work

Research must be done in order to select the set of basis functions which will most closely represent the observed edges of interest. We are currently working on a linear combination of a shifted Gaussian and hyperbolic tangent, which seem to be adequate. Another problem will be to determine the parameters of these functions. We represent the problem as a supervised pattern recognition problem, where during the learning phase the system is shown a number of pixels that are edges, and the parameters are calibrated accordingly. Then, in the recognition phase, these parameters are substituted in the basis function and are used to determine for each pixel whether or not it is an edge.

The pixels thus identified constitute the contour of the cortical bone and any orthopedic implants. These points may serve many functions. First, they may as anchors for traditional orthopedic measurements. The angle of curvature of the spine is one such measurement. Alternately, objective measurements such as cortical area may made where previously subjective interpretation was thought to be adequate. In both cases, great precision is brought to bear upon the decision process. The numbers obtained from the computer radiograph may be at odds with those determined by the physician by hand. Hence, inter-observer variation will still exist. However, the issue of intra-observer variation is essentially eliminated.

As the computer can be taught to recognize landmarks, there are two additional benefits that may accrue. First, standard measurements will require less of the physicians time. Additionally, new measurements may be tested for their clinical utility. In this sense, we hope that our measure of cortical area will largely replace the subjective measure of bone quality. Ultimately, the quality of medical care will be improved.

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