Towards Objective Measurements from Medical Radiographs

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

January 20, 1993

Abstract

Standard radiographs provide a significant amount of information for the orthopaedic 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.

Our process has evolved through six basic, partially overlapping steps. The image is digitized. A three dimensional model is applied to the two dimensional image to reduce the noise generated by soft tissues. A three dimensional model is used to identify the bony contours. The edges are identified. The image is edited. Lastly, measurements are made.

This work concentrates on the edge detection step. We first briefly review existing edge detection approaches and show some results of a general, state-of-the art edge detection algorithm applied to a lower back human vertebrae. Since the results do not seem to be clean enough for higher-level interpretation, 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

The discovery in 1896 that "x-rays" could be harnessed to image the internal workings of the body changed forever the science of medicine. This change was perhaps no more profound than in the treatment of bone and joint disorders. Today, an orthopaedic examination is rarely considered complete without radiographs. The orthopaedic 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.

Continuing with the example of scoliosis, there are two main aspects of measurements on the radiograph that, in combination with the patient skeletal age (also estimated from radiographs) that are used to determine the most appropriate treatment. The first of these is the absolute degree of curvature of the spine. A 45% curve in a 10 year old patient probably requires early operative intervention. A 30% curve in a skeletally mature patient rarely requires any treatment. A 30% curve in an adolescent should be watched closely. The second aspect is the progression, or lack thereof over time and several examinations. The adolescent with a 30% curve that progresses should undergo surgery. When measurements are made by hand, most surgeons accept a change of 5% or more as progression as opposed to random variation. It is not hard to imagine the dilemma that arises when a curve progresses from 30% to 34%.

Orthopaedic measurements are not limited to the spine. Some fractures are treatable by casting, others require operative intervention in order to achieve an acceptable result. Part of this decision making process is the displacement of the various fracture fragments. In the case of prosthetic implants, a small change in the position of an implant may herald failure of the reconstruction long before the patient presents with discomfort. Thus, in several aspects of orthopaedics, radiographs are made on a regular basis and decisions regarding treatment are based, at least in part, upon the measurements made from those radiographs.

2 Edge detection techniques

Physical edges of the objects are fundamental descriptions of physical objects as they relate to transitions in surface orientation or texture. 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. As we mentioned, the first step in this complex sequence of operations is to obtain a compact description of the input image. At this early stage of processing, it is essential for the resulting representation to be *complete*, that is, to capture as much as possible of the information in the original radiograph. The other necessary characteristic of the representation is that it be *meaningful*, i.e., make explicit the important properties of the radiographed scene.

Edges are very likely to be projected as changes in the intensity data received by the sensor. It therefore appears that a basic low level or early vision process of a computer vision system is the detection, localization and characterization of the local two dimensional edges in intensity. This is followed by reasoning at higher levels using explicit, domain-specific knowledge, which enables the measurements process.

Most edge detection techniques apply a smoothing process before the extraction of intensity changes. It has been realized that the amount of smoothing can be adjusted by choosing a proper size for the smoothing operator. In many applications, no single scale of smoothing is sufficient.

Multiscale edge detection is accomplished by applying different sizes of smoothing operators to an image before the extraction of the edges, so that we can get a description of the image gray level changes at different scales, eliminate fine scale noise and also separate events at different scales arising from distinct physical processes.

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 therfore extremely sensitive to noise and surface irregularities. A simple extension of this approach is to compute the difference of the average gray levels of the two one dimensional neighborhoods on opposite sides of a point.

$$\left|\frac{1}{\Delta}\sum_{n=1}^{\Delta} g(i,j+n) - \frac{1}{\Delta}\sum_{n=1}^{\Delta} g(i,j-n)\right| = \frac{1}{\Delta}\left|\sum_{n=1}^{\Delta}(g(i,j+n) - g(i,j-n))\right|$$

Averaging over many points reduces the effect of noise to a great extent. Sensitivity to noise requires the inclusion of a smoothing step before differentiation.

A more rigorous approach based on the ideal model of an edge led to the Hueckel operator with the first claim of optimality. Hueckel's approach to edge detection was asking what edge element will best fit the intensities in a given region. Hueckel's model [3] of an edge is a step function F in a circular disc. Let

$$F(x,y,c,s,p,b,d) = \begin{cases} b & \text{if } cx + sy \leq p \\ b+d & \text{otherwise} \end{cases}$$

where the x-y coordinate system has its origin at the center of the circular region. Clearly, there is a 1-1 corespondance between ideal edges F and the quintuples (c,s,p,b,d). Let $E(x,y)$ be an obtained intensity function in the circular disc. Then, we approximate the empirical edge element E with the ideal edge F', that minimizes the distance between E and F', i.e., we minimize $\int\int [E(x,y) - F(x,y,c,s,p,b,d)]^2 dxdy$.

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. Let $H_{i\,i=o}$ be the basis. Then define

$a_i = \int H_i(x,y)E(x,y)dxdy$

$S_i = \int H_i(x,y)F(x,y,c,s,p,b,d)dxdy$

Notice that the a_i are constants and the S_i are variables. The previous minimization is equivalent to minimizing

$\sum_{i=o}^{\infty}(a_i - S_i)^2$

However, only the first eight coefficients are used because real edges are blurred; blurring removes high spatial frequencies and noise predominates in the high spatial frequencies.

The minimization procedure returns both the best edge and a measure of the goodness of the edge. Possible criticisms of Hueckel's approach are that he offers no analytical model for the relationship between the noise process and noise level and the performance of the operator. Therefore, one cannot qualititatively determine a priori the error rates of the operator, or any other measures of its sensitivity.

More claims of optimality have been made by Marr and Hildreth [8], extending the initial work of Marr and Poggio, and the edges from this detection scheme have become a standard gauge against which all other methods are compared. The basic approach is to convolve the image with a rotationally symmetric Laplacian of Gaussian and to locate zero crossings of the convolution. In other words, they propose using zero crossings of the operator $D^2G(x,y)$ on the given image, where G(x,y) is a 2-D Gaussian distribution and D^2 is the second derivative operator for detecting intensity changes in the image . For the sake of reducing computations, the operator D^2G is replaced by the rotation invariant operator $\nabla^2 G$, where ∇^2 is the Laplacian. By using $\nabla^2 G$ with different widths, zero crossings of $\nabla^2 G$ are obtained at different scales, and methods to combine these edge outputs for feature extraction were suggested.

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 points out that better results may be obtained by using two directional filters with directional derivatives especially in the neighborhood of corners. Other approaches have made claim of optimality or shown results subjectively comparable or superior to the Marr-Hildreth zero crossing detector. Several of these approaches are listed below.

(1) 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.

(2) Canny [2] defines certain desirable criteria for edge detection. These include good localization, good detection and a single response to a single edge. 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 . Since it is a first derivative operator, it requires further thinning and thresholding.

(3) 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. They claim better localization than Marr-Hildreth zero crossings detector. On real images, edges are obtained after a few extra filtering steps tuned by the user.

Kwabwe et al. performed edge detection on hand radiographs as a step toward the recognition and measurements of the various bones. Their technique involved global thresholding on the bone-to-flesh transition to produce a binary image of the bone structure, followed by a gradient operation in a 3*3 pixel region. Chain codes, generated from the edge detected image were then used to form a polygonal approximation of the bone structure. Strong a priori knowledge of the bones of the hand was used to classify the approximations according to the various bone types.

The maxima of gradient or zeros of the second directional derivative along the gradient are a natural way of characterizing and localizing intensity edges. This is the basis for two differents methods implemented on the Khoros computer system [7]. The first one, called the GEF method (First Derivative Operator for Symmetric Exponential Filter), uses the first directional derivative operator and approximates the gradient vector for every point in the image. The second one, called the SDEF method (Second Derivative Operator for Symmetric Exponential Filter), detects edges from the zero crossings of the second directional derivative along the gradient direction.

The following three figures were obtained by the KHOROS computer system. Figure 1 is a radiograph of a lower-back human vertebrae, scanned at 240 DPI. Figure 2 is the same radiograph after enhancement by histogram stretching. Figure 3 is the result of the SDEF method applied to the image shown in Figure 2.

3 A pattern-recognition approach to edge detection

Edges in radiographs present a more complicated problem than identifying a step function. Figure 3 demonstrates that even applying the most advanced techniques still does not yield results that enable us to advance to the level of higher imgae understanding. We therefore propose here a basis for a model for detection of bone edges.

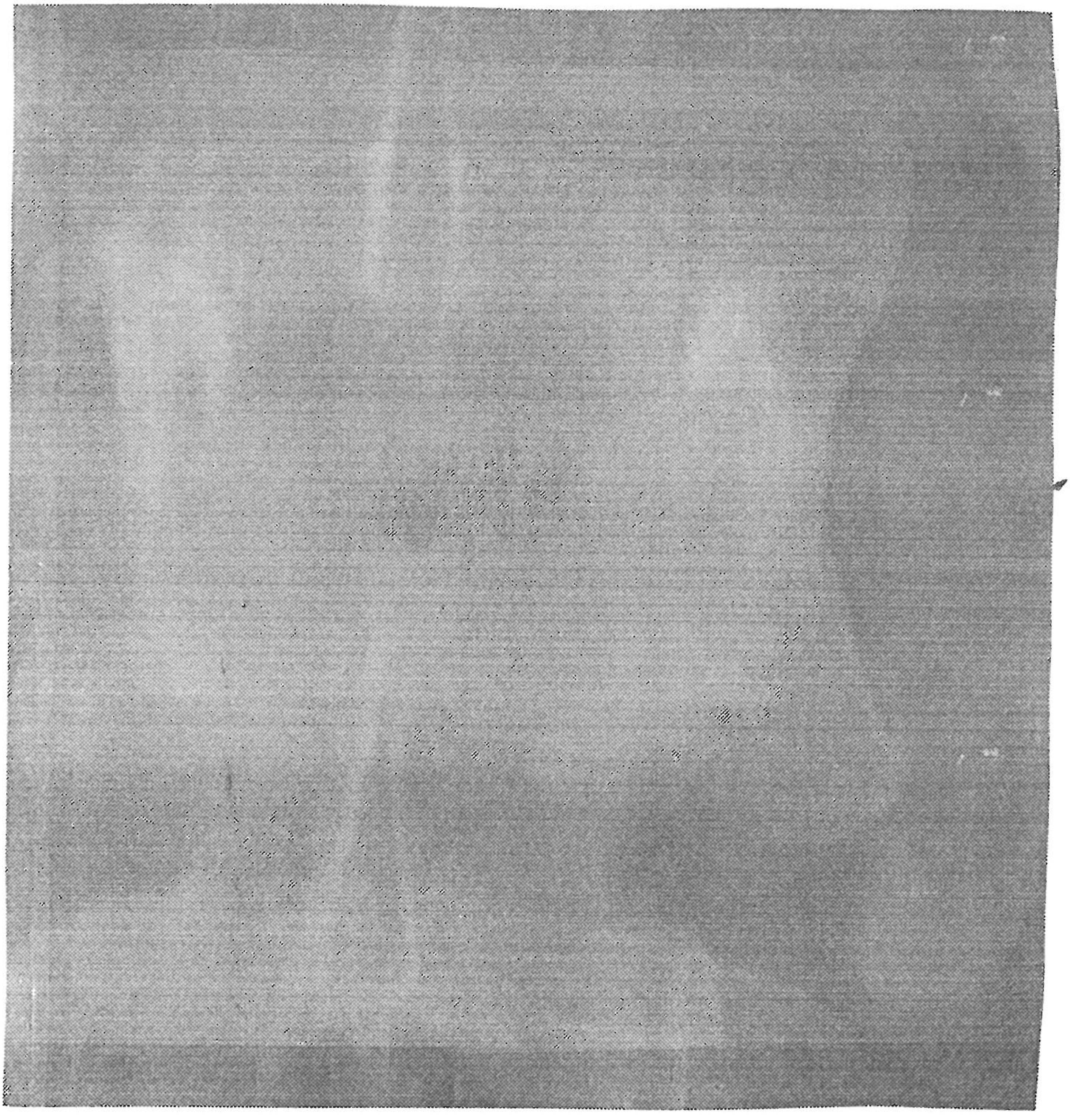

Figure 1: Radiograph of a lower-back human vertebrae scanned at 240 dpi

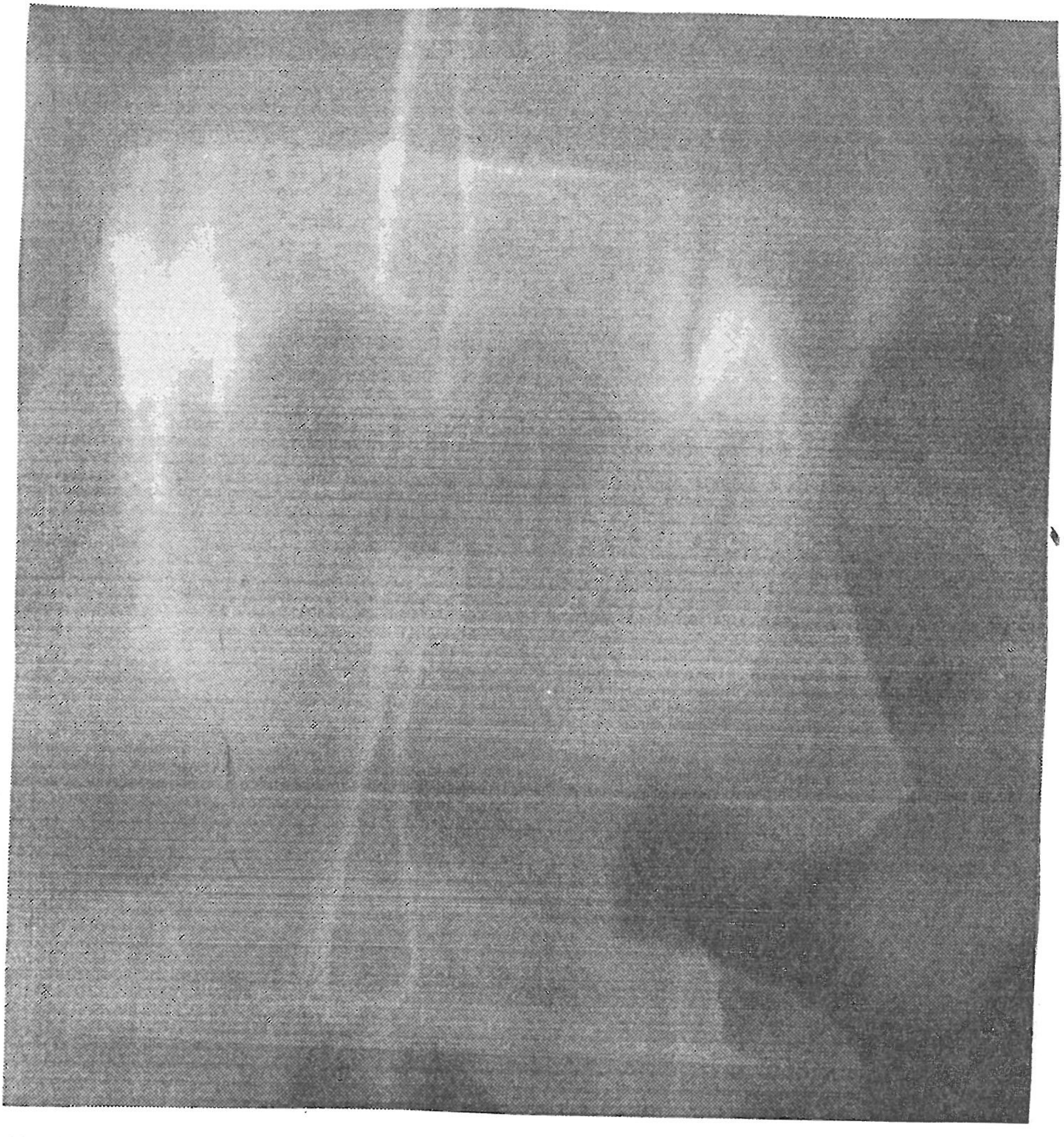

Figure 2: Figure 1 after histogram stretching

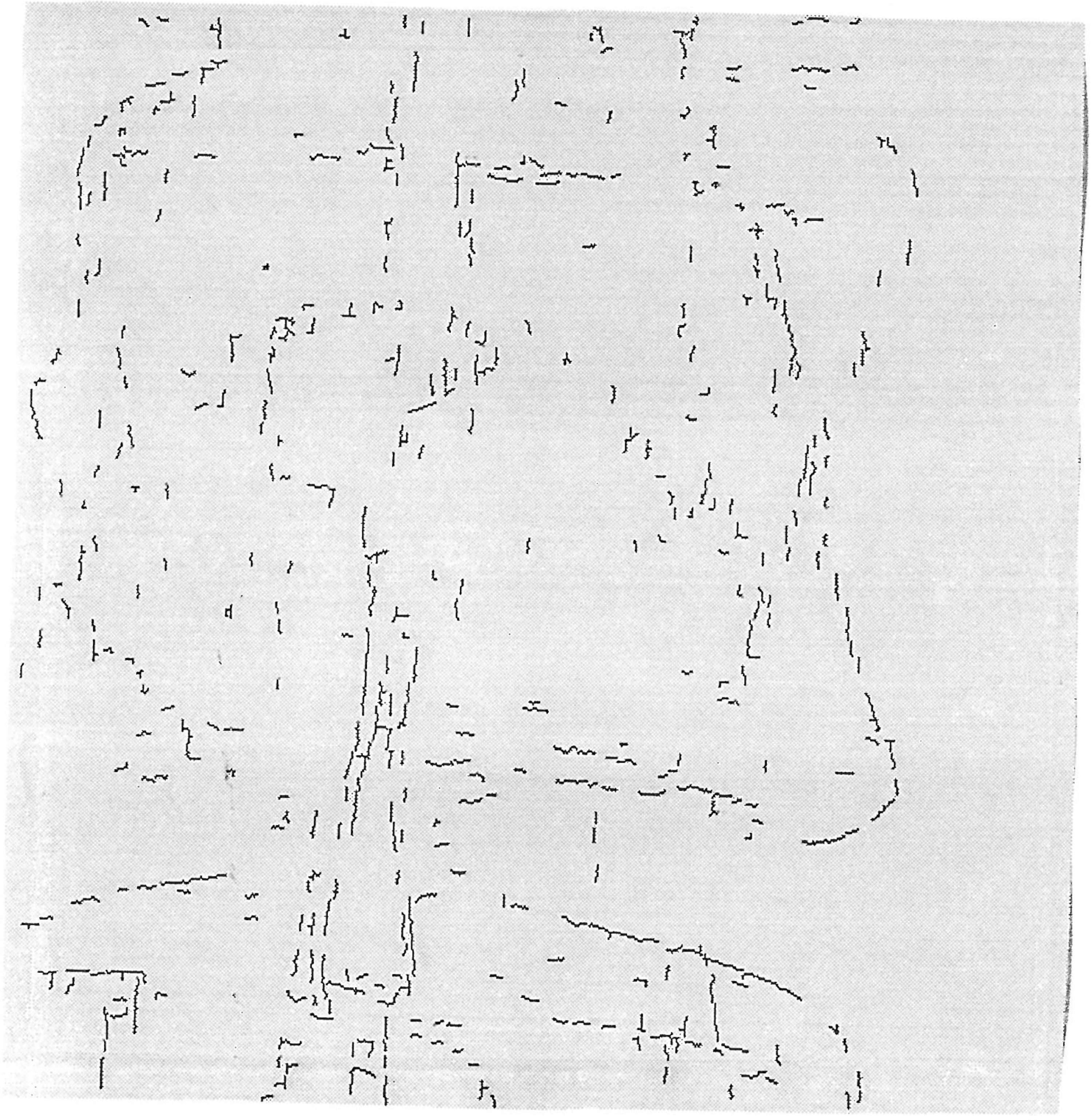

Figure 3: Figure 2 after application of SDEF edge detection method

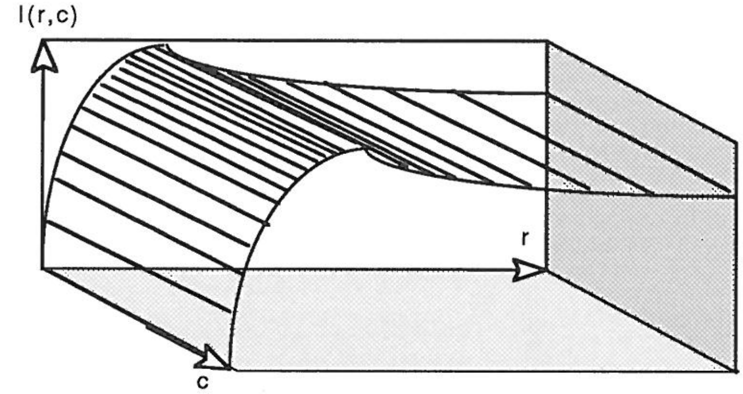

Figure 4: Radiation intensity through a schematic section of a bone

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.

$$I(x) = \sum_{i=1}^{n} b_i B_i(x_i) = (b_1, b_2, b_3 \ldots b_n) \left\{ \begin{array}{c} B_1(x_1) \\ B_2(x_2) \\ \vdots \\ B_n(x_n) \end{array} \right\} = bB(x) \tag{1}$$

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 4 depicts the edge model in 3D space, where (r, c) is the image plane (rows and columns of pixels) and the third dimension is the image intensity for each pixel. In figure 4, 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 5.

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.

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

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

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

and

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

A unit vector is:

$$\vec{g} = \frac{\left\{ \begin{array}{c} \frac{\partial I(r,c)}{\partial r} \\ \frac{\partial I(r,c)}{\partial c} \end{array} \right\}}{\sqrt{\left(\left(\frac{\partial I(r,c)}{\partial r}\right)^2 + \left(\frac{\partial I(r,c)}{\partial c}\right)^2 \right)}} = \frac{\sum_{i=1}^{n} b_i B_i{}'(rcos(\theta) + csin(\theta)) \left\{ \begin{array}{c} cos(\theta) \\ sin(\theta) \end{array} \right\}}{\sqrt{\left(\left\{ \sum_{i=1}^{n} b_i B_i{}'(rcos(\theta) + csin(\theta)) \right\}^2 (cos(\theta)^2 + sin(\theta)^2) \right)}} = \left\{ \begin{array}{c} cos(\theta) \\ sin(\theta) \end{array} \right\} \tag{5}$$

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:

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

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.

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

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:

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

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:

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

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 5.

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

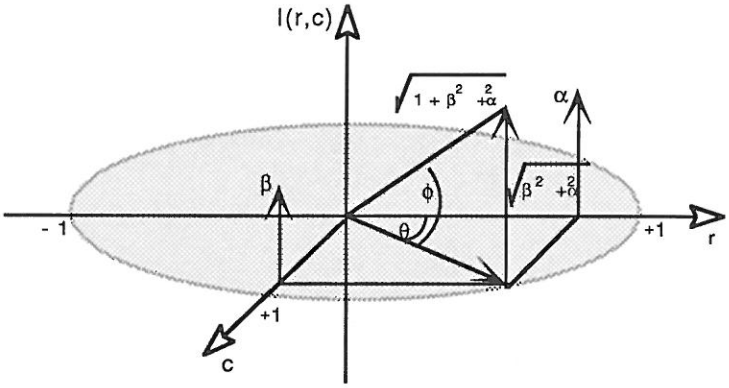

Figure 5: Inclination and gradient directions of unit vector

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

$r = \frac{\alpha}{\sqrt{\alpha^2+\beta^2}}$, 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 5. 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:

$$\phi = \tan^{-1}\sqrt{\alpha^2+\beta^2} = \tan^{-1}\sqrt{(\sum_{r,c} I(r,c)r)^2 + (\sum_{r,c} I(r,c)c)^2} \tag{16}$$

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 adequte. 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 orthopaedic implants. These points may serve many functions. First, they may as anchors for traditional orthopaedic 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.

References

[1] Ambrose, A.R., Edge Detection in Anterior/Posterior Radiographs of the Hip,*Thesis work from Clemson University*,May 1991.

[2] Canny, J.F., Finding Edges and Lines in Images,*MIT Artifitial Intell.Lab., Tech.Rep.720*,June 1983.

[3] Davis, L.S., Survey of Edge Detection Techniques,*Comput. Graphics Image Processing*,April 1975, Vol.4, pp.248-270.

[4] Haralick, R.M., Zero-crossing of Second Directional Derivative Edge Operator,*IEEE Trans.Pattern Anal. Machine Intell.*,Jan 1984, Vol.PAMI-6,no.1, pp.58-68.

[5] Harris, W.H., Traumatic arthritis of the hip after dislocation and acetabular fractures: treatment by mold arthroplasty, an end-result study using a new method of result evaluation, *J. Bone and Joint Surg, 51-A(4)*,1969,pp.737-755.

[6] Harris, A.I., Dori, D., Sheinkop, M.B., Berkson, E. and Haralick, R.M., Automating Measurements from Standard Radiographs, *Proc. SPIE Conference Technology '92 - Intellegent Robotics and Computer Vision*, Boston, Nov. 16-20, 1992.

[7] Castan, S., Second Derivative Operator for Symmetric Exponential Filter,*Khoros System.*

[8] Marr, D., Hildreth, H., Theory of Edge Detection,*Proc.Roy.Soc.London*, 1980, Vol.B207, pp.187-217.

[9] Nevatia, R., Bavu, K.R., Linear Feature Extraction and Description,*Comput. Graphics Image Processing*, 1980, Vol.13, pp.257-269.

[10] Shen, J., Castan, S., An Optimal Linear Operator for Edge Detection,*in Proc. CVPR-86,Miami Beach,FL*, 1986, pp.109-114.

[11] Torre, V., Poggio, T., On Edge Detection,*IEEE Trans.Pattern Anal. Machine Intell.*,Mar 1986, Vol.PAMI-8, pp.147-163.