



COMPUTER AIDED LONG-BONE SEGMENTATION AND
FRACTURE DETECTION

by

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Dedicated to Adam Lane.

You will always be remembered.

Abstract

Medical imaging has advanced at a tremendous rate since x-rays were discovered in 1895. Today, x-ray machines produce extremely high-quality images for radiologists to interpret. However, the methods of interpretation have only recently begun to be augmented by advances in computer technology. Computer aided diagnosis (CAD) systems that guide healthcare professionals to making the correct diagnosis are slowly becoming more prevalent throughout the medical field.

Bone fractures are a relatively common occurrence. In most developed countries the number of fractures associated with age-related bone loss is increasing rapidly. Regardless of the treating physician's level of experience, accurate detection and evaluation of musculoskeletal trauma is often problematic. Each year, the presence of many fractures is missed during x-ray diagnosis. For a trauma patient, a mis-diagnosis can lead to ineffective patient management, increased dissatisfaction, and expensive litigation. As a result, detection of long-bone fractures is an important orthopaedic and radiologic problem, and it is proposed that a novel CAD system could help lower the miss rate. This thesis examines the development of such a system, for the detection of long-bone fractures.

A number of image processing software algorithms useful for automating the fracture detection process have been created. The first algorithm is a non-linear scale-space smoothing technique that allows edge information to be extracted from the x-ray image. The degree of smoothing is controlled by the scale parameter, and allows the amount of image detail that should be retained to be adjusted for each stage of the analysis. The result is demonstrated to be superior to the Canny edge detection algorithm. The second utilises the edge information to determine a set of parameters that approximate the shaft of the long-bone. This is achieved using a modified Hough Transform, and specially designed peak and line endpoint detectors.

The third stage uses the shaft approximation data to locate the bone centre-lines and then perform diaphysis segmentation to separate the diaphysis from the epiphyses. Two segmentation algorithms are presented and one is shown to not only produce better results, but also be suitable for application to all long-bone images. The final stage

applies a gradient based fracture detection algorithm to the segmented regions. This algorithm utilises a tool called the gradient composite measure to identify abnormal regions, including fractures, within the image. These regions are then identified and highlighted if they are deemed to be part of a fracture.

A database of fracture images from trauma patients was collected from the emergency department at the Flinders Medical Centre. From this complete set of images, a development set and test set were created. Experiments on the test set show that diaphysis segmentation and fracture detection are both performed with an accuracy of 83%. Therefore these tools can consistently identify the boundaries between the bone segments, and then accurately highlight midshaft long-bone fractures within the marked diaphysis.

Two of the algorithms—the non-linear smoothing and Hough Transform—are relatively slow to compute. Methods of decreasing the diagnosis time were investigated, and a set of parallelised algorithms were designed. These algorithms significantly reduced the total calculation time, making use of the algorithm much more feasible.

The thesis concludes with an outline of future research and proposed techniques that—along with the methods and results presented—will improve CAD systems for fracture detection, resulting in more accurate diagnosis of fractures, and a reduction of the fracture miss rate.

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Declaration

I certify that this thesis does not incorporate without acknowledgement, any material previously submitted for a degree or diploma in any university, and that to the best of my knowledge and belief it does not contain any material previously published or written by another person, except where due reference is made in the text.

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Note about the images

All the x-ray images shown in this document have been modified by inverting their brightness to make them clearer when printed on paper. As a result, dense regions such as bone tissue appear darker rather than lighter.