**Comparison of the Expectation Maximization Algorithm and an Artificial Neural Network for Automated Bone Segmentation**

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**Introduction:** Computed tomography (CT) and magnetic resonance (MR) have been applied extensively to study the human skeletal system. These imaging modalities allow for the creation of three-dimensional bone models from segmented regions of interest. These models provide a means to perform engineering analyses and to optimize individualized orthopaedic surgical procedures. Often the segmentation process can be time consuming, thereby precluding analysis on a patient specific basis. Many techniques have been used to segment regions of bone from the various imaging modalities. Traditionally, manual raters have performed segmentation of bone from medical images. This time-consuming process has motivated researchers to improve its efficiency and accuracy by automating this process. A variety of methods have been attempted including: thresholding, region growing, atlas based, artificial neural networks (ANN), and various combinations of these techniques. Researchers have surveyed a variety of bony regions of interest including the acetabulum, femur head, cranium, pelvis, carpal bones, mandible, vertebrae, and ribs. This study aims to develop a segmentation method to accurately, efficiently, and reliably separate bones from CT images.

**Materials and Methods:** Two different segmentation techniques, Expectation Maximization (EM) and artificial neural network (ANN), were applied to segment the phalanx bones of the hand. Fifteen cadaveric specimens were scanned using a Siemens Sensation 64 slice CT scanner (Matrix = 512x512, FOV = 172x172 mm, KVP = 120, Current = 94 mA, Exposure = 105 mA) with an in-plane resolution of 0.34 mm and a slice thickness of 0.40 mm. The phalanx bones of the index finger from each hand were manually traced. Five specimens were dissected and the excised proximal, middle, and distal phalanx bones of the index finger bones were scanned using a laser scanner. To simplify our registration and segmentation techniques, the left hands were transformed into right hands by mirroring the images along the x-axis. The first step in the segmentation process was registration. One specimen was chosen as the atlas image. Registration between the atlas image and the individual specimens was performed using a three stage technique including landmark identification, thin plate spline registration, followed by a higher order Thirion transformation. The atlas image was warped to each of the specimens. The manually defined regions of interest for the atlas image were smoothed with a 4mm isotropic gaussian filter. The resulting images were then warped to each specimen using the deformation generated by warping the atlas image and used as probability information for the EM algorithm [1]. The algorithm also utilized an estimate of the mean and covariance for each of the regions to be segmented. A post processing module was designed to remove isolated island voxels and to produce solid models. The ANN algorithm [2] was the second segmentation algorithm applied to this data. Using seven sets of the manually traced images, the neural network was trained to recognize the various phalanx bones of the index finger using probability and signal intensity information. The ANN was then applied to the remaining eight subjects.

Both segmentation algorithms (EM and ANN) were compared to the manual segmentations using a relative overlap metric, volume(intersection)/volume(union), measured using the BRAINS2 software package [3]. A Euclidian distance map between the laser scanned surface representation and a surface model generated from the automated segmentation was created using the IA-FEMesh software for each specimen.

**Results:** A prior study by our laboratory validated the manual tracing method as a means of segmentation [4]. Our results show a relative overlap of 0.87, 0.80, and 0.70 for the proximal, medial, and distal phalanx bones using the EM technique. The ANN had similar overlap metrics: 0.87, 0.82, and 0.76. An example of the resulting segmentation using the EM algorithm is shown in Figure 1.

The average distance between the surface scan and the resulting model generated from the EM based segmentation was 0.31, 0.34, 0.51 mm for the proximal, medial, and distal phalanx bones. The average distance for the ANN was slightly smaller: 0.18, 0.26, 0.38 mm. The EM segmentation improved on the efficiency of the manual techniques by a factor of 12 and the ANN segmentation improved by a factor of 32.

**Discussion:** This work shows that the EM and ANN based algorithms performed similarly in their ability to segment the phalanx bones from CT images of the hand. The same registration algorithm was used for both segmentation techniques allowing us to directly compare the underlying algorithms. The relative small size of the distal phalanx and its greater anatomic variability made automated segmentation of this region more difficult. Future work will focus on refining these algorithms by optimizing the registration step and possibly including shape priors into the segmentation algorithm.

**References:**
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