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Model-Based Interpretation of Chest X-Rays

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Abstract

An "expert assistant" system has been designed to recognise basic anatomical features in anterior-posterior X-ray views of the chest. The long-term aim is to develop a model-based interpretation methodology which may be applied to other imaging modalities and anatomical regions. Key features of this methodology include a three-dimensional anatomical model, an inference engine, image-analysis and visualisation tools and an overlying control structure. The anatomical model is object-centred, incorporating shape and connectivity information, and is designed to accommodate normal and disease-related variations. The inference engine incorporates into its model previously located structures for the identification of further structures. A preliminary version has been implemented using frame- and blackboard-based architecture.

1. Motivation and Goals

The Medical Image Understanding (MIU) project aims to provide "expert assistance" for radiologists in the context of high-throughput, digitally based Radiology Departments. This is achieved through model-based automatic analysis of images to provide "alerts" for abnormalities [1] and decision support for equivocal diagnoses [2]. An important design criterion for such a system is the ability to incorporate heterogeneous information sources, such as images formed from different imaging modalities and non-imaging sources. Simple image registration is not possible for many imaging modalities, for example, if a diagnosis is to be performed using images made by projection (such as X-rays) and sectioning (such as ultrasound). In this case both the image-formation physics and the image geometry make direct image comparison impossible. Another aim of this project is to explore image-understanding algorithms which may be applied to different anatomical regions. Many of these aims are achieved by basing image analysis on separable models of anatomical structure and image formation, and by performing data fusion in the domain of actual anatomy.

Many of the ideas inherent in the Medical Image Understanding concept are being incorporated in a demonstration project restricted to one anatomical region and, initially, to one imaging modality. Chest X-rays have been chosen for this initial study, because they represent a common diagnostic problem where expert assistance might improve diagnostic accuracy, and the projection imaging technique requires a complete anatomical model for image interpretation.

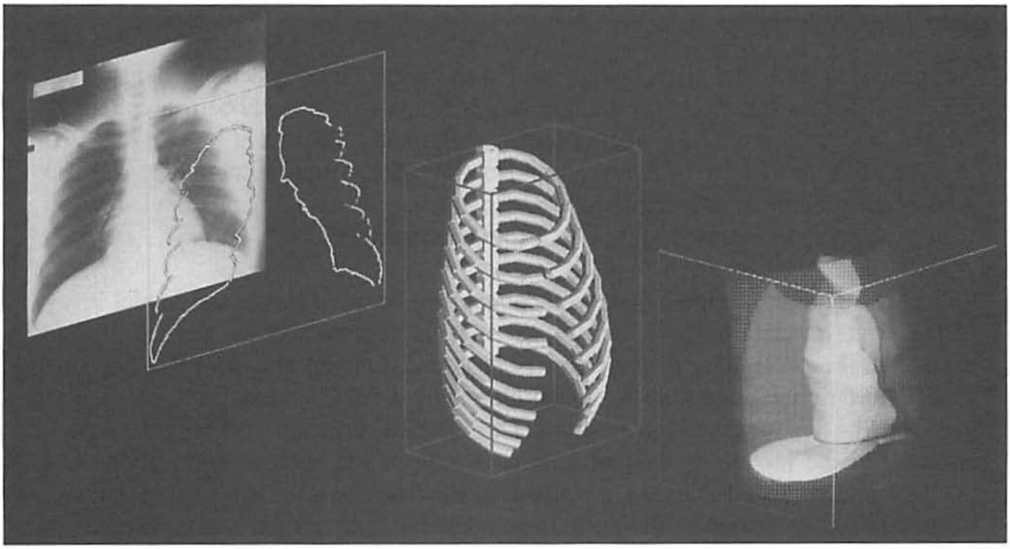

Fig. 1: Examples of the principal elements of the Medical Image Understanding chest X-ray analysis system. Left to right: original X-ray image; derived features of the image, in this case lung outlines; visualisation of a 5-parameter model of the skeleton fitted to the X-ray image; visualisation of a soft-tissue model including pleurae, diaphragm and mediastinum.

2. Methodology

The central feature of the MIU methodology is an object-centred, three-dimensional, deformable description of human anatomy, since the anatomical model is thought to be the paradigm for expert analysis of medical images. This description assists in (a) guiding image segmentation by predicting features based on current instance information [3] [4], (b) checking for abnormalities and (c) visualising the resulting instantiated anatomy. The model is sufficiently explicit to permit precise prediction of features such as the edges of specific organs. The interaction between image and model is via a feature space:

$$\boxed{\text{IMAGE SPACE}} \longleftrightarrow \boxed{\text{FEATURE SPACE}} \longleftrightarrow \boxed{\text{ANATOMICAL SPACE}}$$

"Anatomical space" refers to a description of anatomy, both normal and abnormal, which may be varied to maximise the fit between model and image(s). Image space is the pixel space, which may include multiple image modalities. Feature space includes symbolic descriptions of image features (such as edges and textures) derived from model and image space.

3. Preliminary Experimental System

The proposed methodology is being tested in an experimental system developed on a Silicon Graphics Indigo2 workstation using a frame-based blackboard architecture written in C and Lisp. This paper describes preliminary analysis of images digitised to 8 bits and up to 1K by 1K resolution from anterior-posterior chest X-rays. The goal of the preliminary system is to locate features using anatomical knowledge and then perform some simple tests to check for abnormalities.

Object recognition is edge-based, with comparison between image and model being carried out in feature space, where an edge is represented by connected line segments. For simplicity the preliminary anatomical model also uses line segment models to describe edge shapes, though ultimately a full 3D model will be used to generate the feature-space elements. The expected direction and length of each segment in the model, as well as relational information such as connections and position relative to other edges, are stored in the frame system [5]. This relational information is described explicitly in the model, and is translated into constraints in the feature space.

3.1. Control Architecture

The control architecture uses a blackboard [6] to store the contents of the feature space. The blackboard consists of two types of frames:

1. Model frames, each containing a line segment translated from an edge in the model into the feature space. Intrinsic and relational knowledge about the edge are translated into constraints on the position, length and orientation of the corresponding line segment.
2. Instance frames, each containing pixel coordinates which are candidates to be matched to a given line segment, i.e. they are instances of the edges predicted by the model.

The blackboard also contains the instances which are currently considered to be the best match to the model. Each instance frame has a confidence score based on how well it satisfies the constraints given by its model frame.

3.2. Major Landmarking

To provide initial guidance to the segmentation, some major landmarks are identified first. The midline is found using a symmetry-detection algorithm [7]. The approximate boundaries of the body, lungs and ribs are then found using a variety of segmentation techniques, such as seeded region growing [8] and thresholding [9].

Since the edges in the image are inter-related, new edges found with high enough confidence are used to update relational constraints on other frames. Backtracking is likely to introduce convergence problems and be computationally intensive, and so it is limited by grouping mutually dependent edges, such as connected edges, and permitting backtracking within, but not between, groups.

To recognise a group of edges, the first step is to perform edge detection on the image to create a set of candidate edges (instance frames) for each model frame. Combinations of the candidates can be examined using backtracking to find the set which yields the highest confidence. There are two elements to the strategy for finding groups:

1. Careful choice of the order in which the groups are found. Groups which are independent of others, and those for which the related groups have already been found, are generally processed first.
2. When imposing constraints on a group via its relationship to another group, attention is paid to the confidence with which that other group was found.

After matching the line-segment model to the image, actual pixel boundaries can be located by performing local edge detection near the line segments.

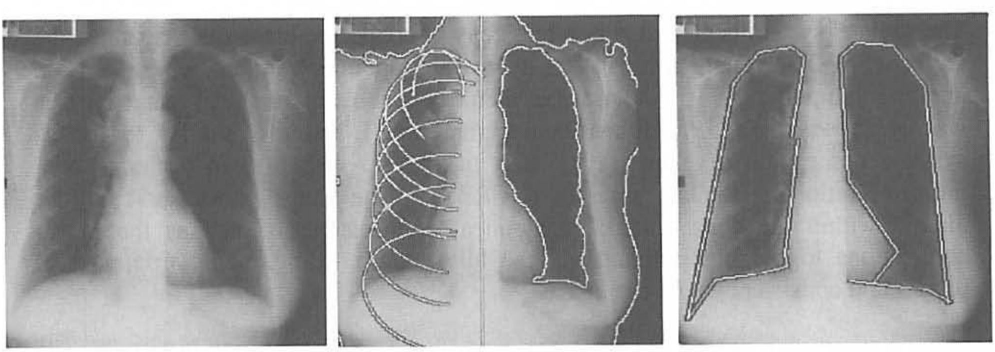

Fig. 2: Initial landmarking and fitting of line-segment model. Left to right: original X-ray image; midline and initial rib and lung landmarking; line-segment model fitted to lung, diaphragmatic and mediastinal borders.

The above strategy is used for landmarking lungs, mediastinum and diaphragm. An important feature of chest radiographs is the depiction of ribs, and our project aims to identify each rib using an explicit anatomical model. This will be used for fixing parameters in the 3D anatomical model. Several techniques have been investigated for identifying ribs in these images. For identification of incorrect patient positioning it is necessary to match images of anterior and posterior rib segments. This is done by fitting curved segments to the intersections of the rib images with the lateral margins of the lungs, the continuity of the rib image providing the information which links the anterior and posterior rib segments. A full, 3D rib model now under development will permit more complete identification of skeletal structures, and information on patient positioning. This skeletal model, together with major soft-tissue landmarks, will assist in locating more subtle image features.

3.3 Three-dimensional Model

The requirements of the model are served through an object-centred anatomical description being developed in parallel with the image processing and control structures. Anatomical descriptions are incorporated into the frame structure used in the image analysis system described above. Information stored in the slots for each organ, or part of an organ, includes location in a prototype anatomy, shape descriptors, inherited parameters, imaging properties (e.g. X-ray density), connections to other organs and adjacency relationships.

Slightly different descriptors are used for the skeletal system and soft organs, because of the different constraints imposed upon them. The parameters of the skeletal system are determined directly from the image, and are not subject to a space-filling constraint. However, soft-organ size and shape are partly determined by space-filling and adjacency constraints, i.e. all internal body spaces are filled, but no two organs can occupy the same volume.

The skeletal system is modelled as a hierarchy of connected elements, starting at the C7 vertebra. Each element consists of a rib, rib segment or vertebra, whose location and orientation depends on the previous element. Such a hierarchical representation was achieved using three-dimensional parametric, L-systems, similar to the L-systems description of plants [10]. Soft tissues are described in terms of non-uniform, rational, B-spline surfaces (NURBS). The shape parameters may be altered within the constraints of anatomical connectedness (such as the lungs-connections to the mediastinum via the hila), space filling, non-overlapping of organs and consistency with the image.

The symbolic linkages inherent in the object-oriented structure of the anatomical model permit consistent variation of model parameters to fit images, or simulated effects of specific diseases, while its explicit 3D structure facilitates generation of feature-space information (such as the location of a given edge) which may be compared directly with corresponding features derived from image space.

4. Conclusions and Future Work

Image-processing techniques have been successfully demonstrated for segmenting chest X-ray images, using mainly two-dimensional models for identifying lung outlines and ribs. A frame- and blackboard-based control structure has been created for high-level control of the segmentation and linking to higher level descriptions. A three-dimensional anatomical model has been constructed and is being linked to the image-processing modules via the frame structure, and this will provide guidance for the detailed segmentation of the X-ray images. A logical extension of the project is to include both lateral and anterior-posterior views, which can be compared readily in anatomical space. Because of the anatomical nature of the prior knowledge, the clinical emphasis of the project is on diseases producing structural rather than disseminated or focal change, and on diagnosis based on edge location and characteristics, rather than textural analysis.

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