An Intelligent Visual Task System For Lateral Skull X-ray Images

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This paper describes research into structured, knowledge-based image interpretation. An integrated framework has been developed, within which most tasks associated with the automatic interpretation and analysis of lateral skull X-ray images (cephalometry) can be performed. A model-based image analysis system makes use of a blackboard architecture and multiple knowledge sources. Its performance compares favourably to previously published attempts to automate cephalometric analysis.

Cephalometric measurements, from lateral skull radiographs, can be of help to orthodontists in deciding upon the nature of any necessary orthodontic treatment, or in defining standards for classifying craniofacial growth. Manual and interactive methods of performing the cephalometric analysis are acknowledged as error prone [1,3]. An automated analysis, using computer vision techniques, that could provide systematic and accurate results would be of benefit. Such a system is being developed using knowledge-based methods.

There are a number of different tasks that need to be tackled in developing such a system. Reliable methods need to be implemented to segment individual anatomical features and landmarks. These must be able to extract low contrast features in possibly noisy image areas. We have previously reported one such system with promising results [2], though modifications are required to allow a greater use of feature appearance models. In order to control the segmentation system it is also necessary to generate image areas within which specific features are expected to be located An appropriate declarative knowledge-source, with associated models, offers a satisfactory approach to the problem. The full system must be able to demonstrate various forms of behaviour. A dynamic means of organising image interpretation tasks, allowing for different analyses of the same image, must be present. Alternative solutions to a current task ought to be allowed. This will entail the use of some constraint application method that allows the most viable (ie correct) interpretation to be produced. Blackboard architectures, as developed for solving other complex problems [4] requiring the use of a number of forms of knowledge, offer a suitable framework for organising these tasks. Furthermore it would be sensible to develop the blackboard system within an integrated framework that permits the use of model building facilities, and enables the segmentation system to be used in a stand alone mode. Such facilities can be used to ensure the validity of newly developed models.

Background

A number of automated cephalometric systems have been developed [1,9,12]; the most successful being the Parthasarathy et al [12] algorithmic implementation of the knowledge-based system of Levy-Mandell et al [9]. This system improves on the performance of the original by incorporating lessons that became apparent during the development of the knowledge-based system. The Levy-Mandell system uses an elementary knowledge-based approach that works only on relatively good quality radiographs. It typifies a methodology which has often been applied to medical image interpretation. A high level module is used to model an application, so that particular declarative features can be matched to the results of a rigidly defined low-level segmentation module. The segmentation module typically convolves a low-pass, or smoothed image, with a particular edge operator to produce a list of edge segments. Domain knowledge, usually represented in production rule format or as a structured set of frames, is then applied to interpret the list of line segments.

While such knowledge-based systems have achieved some measure of success the results are heavily dependent upon the preprocessing and edge detection processes. When the chosen operators fail, typically because assumptions about the nature of the image are ill founded, the whole system breaks down and acts in a quite *unintelligent* manner. It has been suggested [5,8,14] that alternative modes of segmentation, involving multiple low-level knowledge-based modules may provide the adaptability required for medical image segmentation.

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Nazif and Levine [11] demonstrated that heuristics, typically used in imperative segmentation systems, can be expressed, to good effect, at the production rule level. Their system perhaps suffers from attempting to provide a too general solution, leading to ambiguities in image interpretation. The SIGMA system [9] makes use of multiple knowledge sources; each with a clearly designated task. It can be seen as an advance on the Nazif system, with modules for segmentation, locality definition and model access. However the nature of biomedical images and the biological variability associated with even the most major of features require more sophisticated constraints and greater subtlety in system control than industrial, machined part or even aerial image systems [14].

Overview Of The Image Reasoning Tool

Our initial experiments with lateral skull X-ray images demonstrated that no sequence of low-level image processing could be guaranteed to provide cues to support the presence of a given feature or landmark.

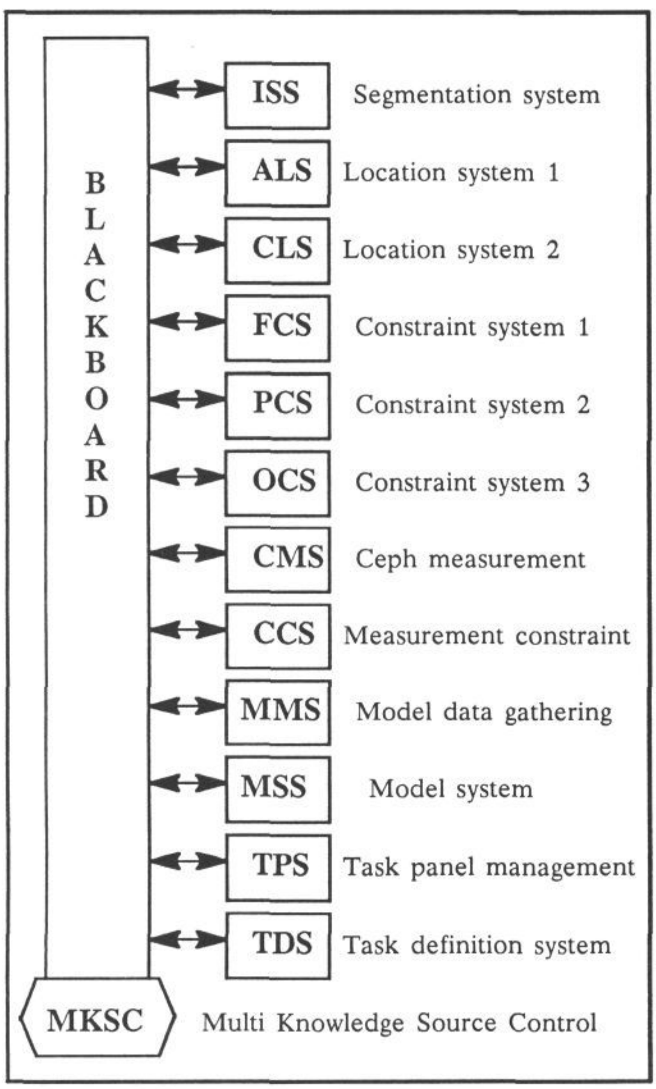

Figure 1 The Stylised Blackboard Architecture

The variations in image quality, both digital and on the X-ray film, and in the subtly varying morphology, shape and visual definition of the biological features sought, suggested a more adaptable approach to the problem would be required.

A model of the lateral view of the head could be developed, using data gathering modules, that would encompass declarative object definitions and statistics for object feature appearance and expected areas of interest within an image. The principle function of such a model would be to enable the image interpretation system to reason about application goals using evidence from the model, and any given images or other sources of information, in order that these goals be satisfied. It is envisaged that at various stages in the chain of reasoning, evidence from the chosen source image would be required, so that hypotheses regarding the location of selected features in the source image could be accepted or rejected. The architecture adopted must offer the adaptability and necessary structures with which to co-ordinate the variety of reasoning tasks required.

Figure 1 depicts the blackboard architecture which has been adopted in this work. Each of the modular knowledge sources, whether declarative or imperative, is designed to undertake specific classes of task. For instance the intelligent segmentation system (ISS) attempts to find image feature objects given an approximate location. Two location systems, both rule based and using the same generic inference engine, are used to generate (ALS) and constrain (CLS) expectation windows for image features. The task panel management system (TPS) accesses areas of the blackboard defining found, found and rejected, searched for but not found, and inactive objects together with a task specification structure, so that a currently active object may be defined. The task specification structure, or task panel hierarchy, is produced by the task definition system (TDS). This frame-based hierarchy is generated from a set of unstructured frames defining object dependencies. The TASK frame, or hierarchy root, becomes the object the blackboard system must ultimately satisfy. By finding objects further down the hierarchy frames are instantiated. The various levels reflect how frames are defined on each other and are not dependent upon the class of frame for any member at any task hierarchy level.

Object Models

A variety of models are present and available for use in the blackboard system. Some are purely declarative, whilst others rely on statistics generated from data gathering modules accessible from within the AITOOL system. A combination of these two classes of models is allowed.

The image feature appearance model mixes both declarative and statistical knowledge. Hence we can declaratively define the curvature of some model primitive as *Convex*, meaning the internal aspects of this curve are of a higher image intensity. We can also generate population statistics from training examples which circumscribe the nature of the curvature and quantify profile characteristics along the curve. Complex features can be built from more fundamental objects in the manner suggested by Tsotsos [12]. This allows models to be built from a base of perceptual (and model) primitives, in a constrained way along representational axes, to form fully specified combinations.

For objects likely to require image segmentation an image location model is provided for use by the automatic location system ALS. Rectangular image regions, or *windows*, can be defined for all features of interest. Statistics can be generated not only for the size (width and height) of these windows, but also for the absolute and relative positions of their centre points.

Further models describe statistical relationships between pairs of features, typically cephalometric points or feature location window centre points. Angular and distance parameters can be generated from data gathered for the feature windows or from windows fitted to previously found features. This relative location model can be used in either location generation by the ALS or in constraint propagation (FCS and PCS). A similar statistical model exists for all aspects of triangles defined on points of window centres, or cephalometric points, and is used in constraint propagation (OCS and CCS).

The Reasoning Cycle

A default blackboard is constructed by calling the blackboard system and image references are written to the blackboard when selected. The system keeps a displayable track of generated windows, and all found, and rejected features. Task selection causes task frames to be loaded onto the blackboard. The task specification system will then create a blackboard task panel from the list of frames or references, within the frames, to objects defined within any of the declarative models. Any frames not used are removed, and any frames containing slots referencing frames not available are redefined without those slots. At this stage all knowledge sources, including the blackboard are fully initialised and image analysis can commence.

The blackboard control system (MKSC) commences a hypothesis and test reasoning cycle, calling upon very general functions in a specified order to interact with the blackboard. Any one of these general functions can cause further, more specific reasoning cycles to be initiated. Objects are selected and predictions, or hypotheses, are generated for the selected object. Candidate objects are found, then tested for validity. In The blackboard can then build a reasoning profile of what objects and systems have been used, what is left to be done, what has been done but proved to be unsuccessful etc. In this way any attempt at finding an object which has already been unsuccessfully searched for, can use more exacting knowledge in successive attempts.

Objects, and current task panel levels, are specified by the task management system (TMS). An object becomes active once selected as the blackboard current object. It remains active until a suitable candidate(s) is accepted by all constraint systems or until objecting constraint systems are overridden. Objects are chosen on the basis of a cost function related to statistical variance. Higher level objects, eg angles, are attributed a cost value related to the objects they are defined upon.

Intelligent Segmentation

An initial implementation of the ISS has been described elsewhere [2]. The current ISS is much improved in computational efficiency and in its functionality. The system now makes no attempt to back chain, but uses model-directed objective-specific forward chaining, with an improved graph-based backtracking mechanism, to find required objects. The rule base places greater reliance on the interaction between image parameters, as gathered by image processing tools within the ISS, and the new format feature appearance models to control, its actions.The production rules, within the segmentation knowledge-base, now take saliency values and a greater wealth of rule syntax is provided. The image processing and segmentation operators are similarly improved, with greater reliance placed on model parameters. The system allows segment splitting and combination, during segmentation, in a model-based manner derived from the Nazif and Levine system.

Segmentation strategy borrows the *Recognition and Identification* analogy used in human perception study [7]. Once the initial selection of binary cues have been extracted from the source image, they are adapted and rejected until the set of objects are statistically *recognisable* as members same class as the modelled feature. Identification allows the system to select the most suitable candidates.

Object Expectation Windows

The automated location system (ALS) is capable of specifying areas of an image likely to contain an object, utilising two of the models introduced above within a declarative knowledge source. This it does in one of two manners; the method used is dependent upon the number of features already found.

If less than two image features are found, the system accesses data defining mean and variance for a window's centre point, and convolves this with the mean and variance for window size. The generated window is written to the blackboard as the expected location area. However if the current feature is not a member of a specified subset of features no location for the feature can, as yet, be given. Typically in such a case, the blackboard task object would be reselected at a later stage in the image analysis, allowing the second mode of location window generation to be used.

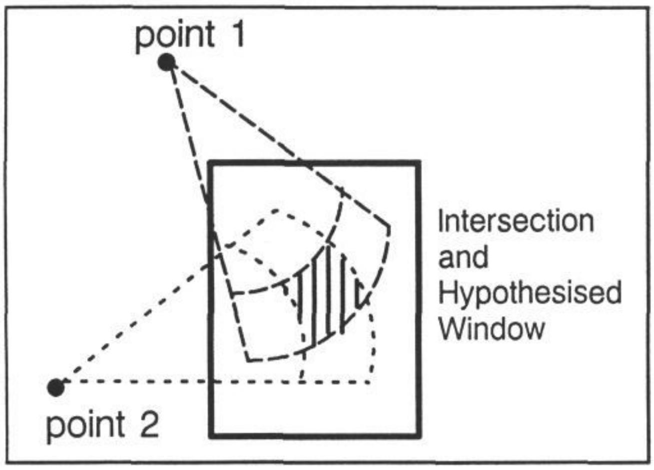

Figure 2. Location Propagation

Where more than two features have already been found, the system uses further geometric constraints to generate areas of intersection between pairs of found features and the required feature. Where a null intersection is generated, the system backtracks to produce the most viable non-null intersection. The result of this constraint propagation can be convolved with location window size statistics to produce an expectation window of use to the rest of the blackboard system (Figure 2).

Cephalometric Measurements

A relatively straightforward imperative system produces lines, ratios of distances and angles according to the specification of the currently selected task panel frame. Angles can be defined upon pairs of lines, line and point (or point and line), and three or four points. Displays allow the user to verify the correct measurement has taken place.

Constraint Systems

The three constraint systems can only be activated by finding a candidate, or series of candidate, object(s). The FCS and PCS systems use similar mechanisms to verify that a new feature, or point, are statistically contingent with already known features. An insufficient fit causes an object to be rejected. Where more than one candidate is acceptable, the most suitable candidate can be selected using all available statistics. The third system (OCS) works in a similar manner for higher order objects (eg lines, angles) but can have quite different consequences. If the current object resides beyond statistical limits, the system can be caused to reappraise the validity of all found objects.

Initial Results

The AITOOL and multi-knowledge sourced blackboard system have been implemented in Sun Common LISP with image processing modules written in Pascal. Initial results for a system designed to locate features have been obtained with X-ray images of varying quality. Figure 3 shows the results of a successful analysis. The display shows 12 found features, their expectation windows and 10 fudicial points defined upon the features.

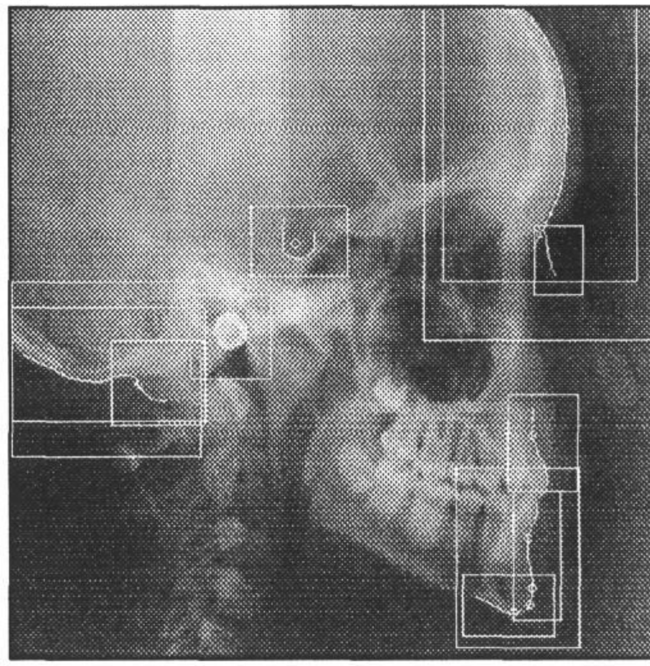

Figure 3. Features found with locations.

The modified ISS, used in interactive mode, now operates with close to 100 per cent reliability. The automatic location system (ALS) is available as part of the blackboard system or in a simplified multi-knowledge (ISS, ALS, FCS, CMS, MSS) sourced image interpretation system (MKSS) which finds features in a predefined order, and has no real task definition knowledge. Results using this system vary with image quality and the probability levels applied. On average it performs with about 80% accuracy, but can run at 100% on good quality images with high contrast features. An initial implementation of the blackboard system is running but requires further development, particularly with regard to the handling of probabilities, constraint values and image interpretation alternatives. Some form of truth maintenance system, or probabilistic belief system is necessary to allow the generation of the most viable image interpretation.

Discussion

Presently the blackboard system is running in an incomplete form, but it does drastically improve on the performance of previous knowledge-based approaches to automating cephalometric analysis. The best procedural solution [12] runs at a slightly higher level of accuracy, but on a narrower range of test images. The present results were gathered using test images that included non-aligned images where double, or incomplete feature stimuli were present, and very poor quality images where a human observer would have difficulty in finding the sought feature.

It should be realised that successful image interpretations are achieved by allowing the system to consider alternative, competitive interpretations. This occurs not only at the gross level where alternative sets of candidate feature combinations exist, but also where alternative interpretations of segments are considered. For instance, it may be possible to generate a set of edge segments in a particular area of the image when seeking the forehead contour. These segments are systematically broken down and combined, using model-based parameters, to offer the greatest possible range of segments. The segmentation phases of recognition, and identification then allow the valid members of this extended segment set to be selected. At a higher level, within the blackboard system's constraint mechanisms, these viable alternative foreheads are considered not only in terms of how well they fit the segmentation appearance model but also, on how these alternatives fit with location models constraining the juxtaposition of different features within an image. Similarly a candidate forehead may be preferentially selected upon evidence related to cephalometric points defined upon the forehead.

It is possible in low contrast, or poorly aligned images for segmentation to initially fail for particular contours. In previous attempts at automating the cephalometric analysis [9,12] this would lead to an image interpretation failure. An initial failure to find a feature, in the present system, causes the selection cost value of that feature to be increased. This allows other features to be found in preference to the failed feature. These found features will then be used in applying greater constraints to the finding of the failed feature when it is reselected as the currently required object. Where such actions still fail, the blackboard system should be able to activate highly sensitive one-dimensional edge evidence collectors. A model-based operator based on the dipole [6] is currently being developed for this purpose. Evidence gathered in such a fashion, together with the model's available to the system, should enable the sought feature to be *inferred*. It should then be possible to perform full automatic cephalometric analyses on even the poorest quality radiographs.

We have chosen cephalometry as our exemplar for the application of knowledge-based and blackboard systems to medical image interpretation, but the types of behaviour displayed by this system should be applicable to other medical or difficult domains. The use of general reasoning methods and the implementation of the system using generic processing should allow the system to be successful in other complex image interpretation domains.

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