Development of a model for use in medical image interpretation

M. G. Cawley and K. Natarajan

Queen Elizabeth Hospital
Edgbaston, Birmingham. B15 2TH

We present here progress on the Alvey MMI/134 project "Model based processing of radiological images". The radiological images we are dealing with are X-ray CT and NMR images of the head.

Radiological interpretation of medical images obtained from any imaging modality, for example X-ray CT, relies on the fact that normal anatomy is predictable with respect to certain landmarks. The radiologist can then take into account variation between normal individuals and the effect of the imaging modality to create a flexible framework with fixed reference points to work from.

We describe here a symbolic frame-based method of modelling 3D anatomy which allows 2D representations to be derived. This slice-wise representation is compatible with both the radiologist's view during interpretation and the images generated by the various imaging modalities.

The types of radiological images[1] produced when scanning the head are static [1] discrete 3-d volume data sets. This 3-d data set is composed of spatially contiguous and aligned 2-d discrete images. Each 2-d image (slice) from the sequence is completely defined by the slice projection and angle, an x,y co-ordinate system with respect to an anatomical co-ordinate reference system, a slice thickness (typically 5mm for X-ray CT) and grey-scale values.[2]

The appearance of anatomical tissue is dependent on the imaging modality used and on the situation the tissue is in. There is no real scope for changing the contrast in X-ray CT other than by use of contrast agents. Thus CT images from a particular scanner are fairly consistent but images may vary considerably between scanners. The problem of interpreting the appearance of tissue is exacerbated in NMR imaging due to the number of parameters associated with each tissue. The appearance of blood, for instance, can change dramatically when flow is present.

When constructing a model[7],[8] for medical image interpretation assumptions can be made regarding the world being modelled. Firstly, the domain under consideration is well structured, with approximate prior constraints on location, shape of 3-d structures. Secondly, the domain can be explicitly described.

Abnormality is described as being an absence, a deformation or a displacement of the normal. This will affect how the anatomy is perceived. Further to this an abnormal feature could be the presence of some additional feature but would be treated in a similar way to normal features that are variable.

In order to interpret radiological images the radiologist/clinician makes use of many types of knowledge acquired through experience. At the simplest level of abstraction the knowledge employed can be conceptually regarded as comprising four parts. These are:

- Anatomical;
- The effect of the imaging modality on the anatomy;
- Non-visual information supplied from previous diagnoses and medical records;
- Radiological expertise, in the form of procedures. This expertise is employed to generate an initial processing agenda.

Static [3] knowledge bases comprising symbolic descriptions have been developed by the authors to embody the first of these three knowledge sources. The anatomical model can be regarded as a static data structure onto which a set of transformations is applied in order to generate a current view of the world, i.e, the appearance of the anatomy under the specific imaging modality given patient details. Radiological expertise corresponds to the control of, and inference strategies on, anatomical, modality and non-visual knowledge. This paper addresses the problem of how to represent the static radiological knowledge sources[4] using a symbolic frame-based system.

ANATOMICAL MODELLING

When modelling the anatomy consideration should be taken of the complexity of the domain, availability and quality of anatomical knowledge, the number of structures and the descriptive and relational properties of the structures[6]. For example, the encephalon (brain) is a complex organ which is, nonetheless, well documented in terms of its structure in stereotaxic atlases. Information about variations within the normal anatomy and the appearance of abnormality is available through consultation with trained members of the medical profession.

Anatomy by its very nature is three-dimensional. Morphological distribution is dictated by the space available and organ function. Within the slice, however, there is little scope for variation, other than normal morphological placing, see Figure 1 for an example[5]. The variations between individuals introduce problems that need to be

[1] In this paper we are excluding temporal image sequences such as cardiology, foetal ultrasound, etc

[2] In X-ray CT the grey levels represent the linear X-ray attenuation of a parallelepiped at position x,y, whereas in NMR the tissue parameters - proton or spin-density, T1 and T2 relaxation, chemical shift and flow - all contribute to the appearance of each pixel.

[3] Static implies that at the time of image interpretation the knowledge cannot be modified, but rather, subjected to transformations in order to generate a dynamic current world model.

[4] Anatomical, modality-dependent and non-visual knowledge sources

[5] This picture was taken from [6]

AVC 1989 doi:10.5244/C.3.55

catered for when generating a 3-d anatomical model. Slice thickness, slice separation and slice angle also need to be taken into account.

Routine imaging of the head most often produces transverse sections, 2-d slices. These 2-d slices are subsequently used by radiologists for interpretation. Therefore an anatomical model must be able to derive 2-d slice instances.

Thus, the anatomical model needs to be 3-d, from which 2-d slices can be reconstructed whilst preserving both 3-d inter-relationships and position within a 3-d reference system.

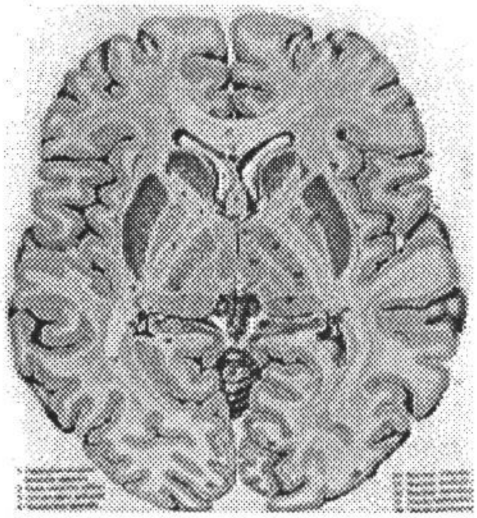

Figure 1: Transverse section through the striate body, the thalamus and the internal capsule corresponding to CT scan angle 0^o.

Deriving a 2-d instance from the 3-d model

The framework for our initial model tries to balance the precision with which we must create our model slices with the variability of normal anatomy. A set of descriptors has been identified which allow for both: relative positioning between features within a coordinate system determined from the head; and relative positioning between arbitrary features:

- left, right, anterior, posterior, above and below are with respect to the coordinate system;
- left of feature, right of feature, anterior to feature, posterior to feature, above feature and below feature are with respect to another feature.

These descriptors are all slice independent and allow positioning in all three dimensions. There are other descriptors which imply some form of cue but are still anatomical. "Next to" implies a distinct change in tissue between features and "merges with" implies the opposite.

The model is split into hypothetical transverse slices, refer to Figure 2. The slice to slice resolution is of the same order as the in plane image pixels. The full head could thus be covered by 256 slices of approximate thickness 1 millimetre. Within each slice the plane is coarsely partitioned into a set of eight strips across the image; these would be coronal sections. The description within the symbolic model will place features in particular strips and slices. For example, the lateral ventricle may appear in strips anterior and posterior *a* and *b*, and slices 50 to 70 inclusive. It is also obvious that the same descriptors

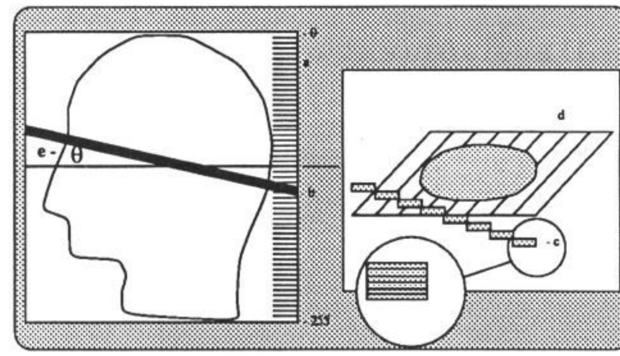

Figure 2: Compiling down a 3-d data set to a 2-d instance

- a - Hypothetical slices are introduced, they are approximately 1mm thick and are contiguous. The anatomy is therefore finely separated in this direction. Each feature specifies which slice it can occur in and relevant parameters within the slice.
- b - The scan information determines which model slices are involved for each image.
- c - The thickness of the scan tells us how many model slices should be included to determine what features are likely to be present.
- d - Coarsely splitting the image into strips means that just the information from that part of each slice can be used.
- e - The angle of the scan determines which slices to include for each strip.

will not necessarily apply to the feature in all the slices. Therefore the slices are allowed to be sub-grouped in accordance with descriptor continuity.

Fine resolution perpendicular to the transverse sections facilitates the amalgamation of model slices to correspond to the real image slices. These slices may in practice be several millimetres thick. For example, the seven model slices 55 to 61 inclusive could constitute the model for use in interpreting a particular CT image. Further to this, if a scan angle other than nought degrees is used, then for each strip position in the model, the set of model slices displaced orthogonally from the transverse which fall on the line drawn at this angle can be used. For instance, a scan at angle θ would have a model comprising of the strips: anterior *a* slices 60 to 65, anterior *b* slices 62 to 67, anterior *c* slices 64 to 69 and anterior *d* slices 66 to 71.

A symbolic hierarchical model of the head

Anatomy can be naturally described in terms of structures and their mutual relationships. The relationships, which may take the form of geometric constraints, can be expressed in terms of symbolic relations. The level of detail needed to define anatomical structures is dependent on the specific task being undertaken. In order to represent the different levels of anatomical detail the model needs to be hierarchical. For example, at a simple level the encephalon can be viewed in the following way:

encephalon comprises
- grey matter
- straight sinus
- glomus
- ventricles
- caudate nucleus
- thalamus
- putamen
- sylvian fissure
- cerebral spinal fluid
- pineal gland
- white matter

Whereas at a more detailed level we find that:

		lateral ventricle
		third ventricle
ventricles	comprises	fourth ventricle
		cerebral aqueduct

and so on. This is represented using the following template:

anatomy((name,parent(group),comprises of([list])))

Finally, at the base of the hierarchy we reach the level at which sub-structures can no longer be decomposed. At this stage the sub-structures are described in terms of identifiable properties. These properties are:

- The position of the structure with respect to a 3-d anatomical co-ordinate reference system;
- Spatial relationships to other structures;
- The nature of the boundary with other structures;
- Shape (at slice level);
- Size (at slice level);
- Tissue type;
- Texture;
- Similarity to other structures.

For example, the anterior horn of the lateral ventricle could be defined as follows:

```
tissue .... cerebral spinal fluid
slices ..... 71 - 150
  position
      inside the skull
      merges with central part of lateral ventricle
      next to white matter
      next to caudate nucleus
  size x% of skull area
  shape ... regional iconic description1
slices ..... 150 - 160
  position
      inside the skull
      merges with central part of lateral ventricle
      next to white matter
  size y% of skull area
  shape ... regional iconic description2
```

This type of knowledge is represented using the following template:

```
anatomy(name,parent(group),
  descriptors([tissue('type'),
    slice([[sl1,sl2],position([list]),size(),shape([block list])]),
    slice([[sl3,sl4],position([list]),size(),shape([block list])]),
  ... )
```

MODALITY-DEPENDENT KNOWLEDGE

Modality-dependent knowledge includes all the factors of a particular imaging modality that affect the appearance of tissue type in the grey-scale image set. Figure 3 is a transverse section of the encephalon obtained from an IGE 8800 CT-scanner at CT scan angle 0^o.

As the various imaging modalities affect the appearance of the anatomy in different ways, it is appropriate to represent this knowledge separately from the anatomical model. For example, in CT the modality-dependent knowledge represents X-ray attenuation coefficients through the use of Hounsfield numbers associated with the component parts of the anatomical model. By divorcing the anatomical model and the modality-dependent knowledge we need only store a static anatomical model which can be subjected to differing imaging modality knowledge.

Information held in a modality-dependent knowledge base include:

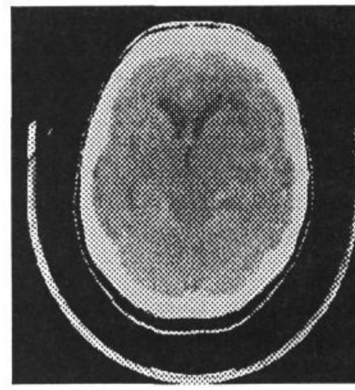

Figure 3: Transverse section showing the anterior horns of the lateral ventricle

- The presence of anatomical structures under the modality;
- The effects of imaging modality parameters (for example, contrast agents) on the visibility, size, shape and grey-level values associated with the anatomical structures;
- The types of artifact and the effect on the image that can occur under the modality;
- Inference about features and their identifiability.(For example, it is fairly difficult to distinguish between grey matter and white matter under X-ray CT);
- Presence and appearance of non-anatomical objects in the image, for example a head rest;
- Attributes of individual scanners.

This type of knowledge is represented using the following template:

```
modality dep(tissue type,parent(group),
 modality([
  CT([attenuation([list of effects of modality
            parameters]),artifacts[],scanner attributes[]),
  NMR([spin density(),T1(),T2(),
        chemical shift()],artifacts[],scanner attributes[])
  ]))
```

NON-VISUAL INFORMATION

The process to this point has been concerned with creating a model which can be mapped into the image domain. It is entirely generic and represents the application of the imaging modality to a "standard human anatomy". Use of this model as it stands should be sufficient to allow a reasonable interpretation. However, useful cues and refinements are overlooked by ignoring the non-visual data[5]. The most obvious case of this is in previous diagnosis of pathology which could markedly alter the structure of the anatomy.

- **Age.** The change in anatomical structure due to ageing is restricted to certain age groups and indeed only applies to a limited number of features. It is not a continuous process and the patient could be well categorised. Tissue on the other hand is much more affected by age. For example the density of bone is known to change with age - relevant to CT, or water density decreasing with age - relevant to NMR.
- **Sex.** The presence or absence of features is designated by the sex of the patient although this is not particularly relevant in the anatomy of the head. Size can certainly be inferred from the sex.

- **Demographic.** As cues to detection of certain pathologies the location of residence of the patient can be used as weighting of pathologies that are known to occur there.
- **History.** This is the medical records for the patient. Information such as previous illnesses and interpretations of scans can be used to prime the model for the current interpretation. History can be split into two sections as follows.
  - **Pathology.** Cues as to alterations in anatomy or appearance of tissues will take precedence over generic information.
  - **Distinguishing features.** If a patient does not appear to fall within the bounds of a particular group then these would be overriding factors and used in preference to the normal definition.

USING FRAMES TO REPRESENT STATIC RADIOLOGICAL KNOWLEDGE

Frames have been adopted as the means of representing the static(declarative) radiological knowledge. The concept of *frames* as a knowledge representation method was developed by Minsky[4] in the mid-seventies, and basically attempts to model human behaviour in terms of standard ways of dealing with familiar situations. Frames provide a mechanism in which both declarative and procedural knowledge can be organised. Frames[2] are organised into hierarchies or networks that can be used to inherit information and can also be linked to *rules*, allowing predicates to be activated when knowledge is stored and retrieved.

Frames can be used to implement much of the functionality of *Object-oriented knowledge representation.* In this representation, knowledge is viewed in terms of a set of objects, each of which is capable of exhibiting certain behaviour. Each object is situated in a network or hierarchy and can access properties and information from higher level objects. One of the main features of objects is that the properties of the object judged to be relevant depend on the situation. This enables frames to be activated using a situation-action control mechanism, i.e a radiological knowledge rule base. Objects provide a powerful style of description, insofar as the description is a process of comparison. Thus, a new object is described by saying in what ways it is similar to, and different from, an already existing object. Another feature of objects is that of *inheritance* and is based on the concept that objects tend to form groups and that members within a group tend to share common properties. By using inheritance we can organise our knowledge in a way that allows the inference of information.

The basic components of frames[3] lend themselves ideally to the problem of representing static radiological knowledge. These components are:

- **Frame name** - Anatomical, modality-dependent and non-visual label for each item of knowledge.
- **Slots/Attributes** - Description of the properties and relationships of frames.
- **Organisation** - Definition of the child-parent relations. In the anatomical hierarchy the parent of the ventricles is the encephalon. Also, the tissue types, grey and white matter have a parent labelled soft brain tissue. Under the CT modality it is very difficult to distinguish grey and white matter, hence the parent definition of soft brain tissue may be used for subsequent image processing.
- **Relations** - The ability to have one frame as the value of another frames' slot. This allows the expression of knowledge such as the similarity of tissues (or structures) with respect to the properties outlined in the section on Modality-dependent knowledge.
- **Constraints** - Enable the inclusion of external parameters through the use of attached predicates. Thus a model can be constrained in light of external knowledge such as the effects of a contrast agent on the image.

SUMMARY

This paper has presented various aspects concerned with the introduction of static knowledge into a hierarchical symbolic frame-based model.

A procedural agenda, acting as a guide for adaptive medical image segmentation, can be usefully produced by the application of radiological knowledge to the three separate static knowledge-bases. This application of radiological knowledge to the static knowledge-bases generates a dynamic current world which is influenced by decisions about the accuracy of the hypotheses used.

The model has been generated for use with X-ray CT and with particular reference to the software environment which has also been created for this project. The model will also be extended to cover other imaging modalities, specifically NMR.

References

[1] **Stiehl, H.S.**, On Spatial Image Sequence Understanding, Technische Universitat Berlin, Fachbereich Informatik, 1987

[2] **Towers S.**, Frames as Data Structures for SBS, MRC CAPCU Internal Report, 1987 (ref: MRC/87/01)

[3] **Parsaye K. and Chignell M.**, Expert Systems for experts, Wiley, 1988

[4] **Minsky M.**, "A Framework for Representing Knowledge",in The Psychology of Computer Vision, P.Winston (Ed.), McGraw-Hill, New York 1975.

[5] **Banks G., Vries J.K., McLinden S.**, Radiologic Automated Diagnosis (RAD),in the Proceedings of the Tenth Annual Symposium on Computer Applications in Medical Care, October 25-26,1986, Washington D.C.

[6] **Nieuwenhuys R., Voogd J., van Huijzen C.**, The Human Central Nervous System: A synopsis and atlas, Springer-Verlag, 1988.

[7] **Newell, J.A., Sokolowska, E.**, "Multi-layered image representation: Structure and application in recognition of parts of brain anatomy", Pattern Recognition Letters, Vol.4, 223-230, 1986.

[8] **Newell, J.A., Sokolowska, E.**, "Model based recognition of CT scan images", Medinfo, 86, 619-623, Elsevier Science Publishers B.V., 1986.