A model for integrating image processing into decision aids for diagnostic radiology

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Abstract

Advances in imaging techniques have been mirrored by advances in the use of computers to extract and interpret image data. Helping clinicians to make effective use of this superabundance of information is a key aim of medical informatics research. One approach is to incorporate digital images and image processing within a knowledge-based decision aid for radiologists. This paper describes a generic design for such aids. The work is based on an abstract model of decision-making which is used to organize the presentation of information from a knowledge base. We describe a system in which the model of decision-making is augmented to describe processes underlying image interpretation. The augmented model, implemented as a logic program, is used to control the application of image processing operators to detect and describe radiological signs. Through the use of this model we are able to combine information from image processing with information from a symbolic knowledge base. The operation of the model is illustrated by considering three different applications in the domain of breast X-rays or mammograms. © 1997 Elsevier Science B.V.

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1. Introduction

Technical advances and technological revolutions are continually improving and extending our ability to obtain information about the body in the form of medical images, to the extent that making effective use of this information is now a challenge. Increasingly these images are captured digitally and presented to clinicians via computer, making computerised decision aids for image interpretation a natural goal of medical informatics research. In a recently published review of this field [26] we applied Wyatt and Spiegelhalter's [31] definition of medical decision systems as 'active knowledge systems which use two or more items of patient data to generate case-specific advice' and identified five kinds of decision support system used in computer aided radiology, each characterised by the use of a different kind of knowledge source: image databases, numerical decision aids, expert systems, image-processing applications and image understanding systems.

No one kind of knowledge source or single class of decision support system is likely to prove preeminent and yet a proliferation of systems would involve redundancy and be confusing and daunting for users. Hence there is a strong argument for developing an integrated decision aid which is able to provide information of different kinds on request, or in response to different problems. This paper argues for the development of systems which are able to draw on information contained in distinct knowledge sources and represented in apparently disparate forms, and proposes a generic architecture for such systems.

Consider briefly the potential for such a system applied to mammography. A radiologist is using a workstation, such as that shown in Fig. 1, to inspect a set of digital mammograms taken following the referral of a patient from the UK's national screening programme. A cluster of microcalcifications is clearly visible on the images and the radiologist must decide whether their form and distribution are characteristic of cancer or one of the benign processes which result in calcification. A computerised decision aid could provide the radiologist with access to a knowledge base representing the best available expertise on the subject, image processing could provide quantitative measurements of image features and a database of digitised images could aid comparisons with images of known pathology. Any decision on the classification of microcalcifications will be followed by a decision on the subsequent course of action, the decision aid could also include a symbolic representation of the hospital guidelines or protocol to be followed in such cases together with a record of the procedures followed in the handling of this particular patient. With the advent of digital mammography all of these can be integrated into a single workstation together with reporting facilities and other tools.

In earlier papers we have identified some of the problems which must be solved for such a system to be developed [26] and proposed a generic architecture for imaging workstations [27]. This architecture consists of three elements: a patient record organised around the use of clinical protocols, knowledge-based decision support and access to imaging and image processing functions. The protocol-based record consists of a representation of the actions carried out in treating a patient, the protocol to be followed and a small set of rules which are used to update a list...
of the actions to be carried out. The knowledge-based decision support uses a model of decision-making processes to organise the presentation of relevant information culled from a knowledge base of medical facts, while the imaging component of the system provides an integrated mechanism for image display and reporting together with a small set of image processing operators to provide additional information.

In this paper we concentrate on a question which has hitherto received scant attention in the literature, the integration of image processing into knowledge-based decision support. Such an integration will allow the decision support component of our workstation to access images as well as the knowledge base and to present decision support based on information drawn from these two sources. In the next section we introduce the symbolic decision procedure used in our decision support tool. We then consider the application of this general procedure to decision-making in radiology and, in the rest of the paper describe an extension to the decision procedure which permits the integration of image processing and knowledge-based decision support.

2. The symbolic decision procedure

At the heart of our system is a version of the symbolic decision procedure developed by Fox et al. [7]. This symbolic decision procedure consists of four elements:
Fig. 2. Applying the decision procedure to the diagnosis of a breast lump. The candidates are the possible causes of breast lump, which include breast cancer. The arguments are provided by the signs and symptoms of breast cancer which include microcalcifications. The eventual decision support will include the evidence for the existence of microcalcifications.

- a set of logical rules describing the process of decision structuring and decision making (generic decision rules);
- a set of facts about different kinds of decision (task specific knowledge);
- a set of facts describing the domain in which the decision is to be made (domain-level knowledge); and
- a set of facts describing what is known about the particular case (case specific knowledge).

The generic decision rules govern the processes of proposing candidates (i.e. possible solutions), constructing arguments (lines of reasoning) for and against the candidates and establishing the existence of the evidence required by the arguments. The task-specific knowledge indicates which classes of the entities described in the domain-level knowledge can serve as candidates and as arguments in the different kinds of decision. Thus the task-specific knowledge instantiates the general rules to form a mechanism for identifying first candidates and then arguments by matching the domain level knowledge to the case-specific knowledge. For example, if the general rules are instantiated with the task-specific knowledge for diagnosis, rules about what constitutes a valid argument for a possible diagnostic solution are used to match domain knowledge about medical signs and symptoms with the case-specific facts, i.e. with what is known about the patient’s problems, as shown in Fig. 2.

The decision support provided by the system consists of the identified arguments for and against each of the identified candidate solutions to the decision problem specified by the clinician. Presenting information in the form of sets of arguments is a powerful technique for the representation of uncertain information [10]. Since a flexible policy may be adopted for the aggregation of arguments, it is particularly suitable for problems where very different forms of information must be considered.
and is a highly promising approach to integrating image processing into a knowledge-based system for radiological decision-making.

The symbolic decision procedure has been used to organise the presentation of decision support in systems developed for domains such as oncology and general medicine [6,29]. In these systems, the decision rules were used in association with facts about the kind of decision and domain knowledge and the process of establishing the evidence required by the arguments was straightforward: either evidence for the required finding was present on a symbolic representation of the patient record or it could be supplied by the user. Our concern in this paper is to consider how evidence may be obtained from image processing operations on medical images. The project within which this work was done seeks to use these ideas to provide support for image interpretation in the context of protocol-based care.

3. Decision-making in radiology

Radiologists are involved in making a wide variety of decisions, both within their own speciality and as part of a team making collegiate decisions. A list of such decisions might include:
- whether or not to recall a client of a screening programme;
- whether or not there is a requirement for further investigations;
- selection of a regime of treatment or surveillance;
- classification of a finding;
- diagnosis;
- staging of a disease; and
- assessment of the response to treatment.

In each of these decisions there is a set of candidates to be considered, potential arguments to be constructed for and against each candidate and required items of evidence to be established. In the example about screening a previously unseen image must be scanned to determine if any abnormality is present. The candidate solutions in this case will include the option of referring the patient, and arguments would be based on the presence of abnormalities on the image and image data suggestive of an abnormality would provide the evidence required. In the staging case an image, which might have already been interpreted, is reviewed in association with other information to establish whether or not the tumour has certain visible characteristics, indicative of the aggressiveness of the tumour. Here the different stages are the candidates, the staging criteria form the arguments and the characteristics are the items of evidence required.

Different decisions involve different ways of interpreting images. We have identified three different interpretative tasks which radiologists have to perform in making the above decisions: detection, classification and measurement. In each task there is a different mix of what is known and what is not known.
Detection: given the image class and the context in which the examination was requested, a set of possible abnormalities is known and, perhaps, a set of possible locations, the task of the radiologist is to assess the evidence that any of these abnormalities are present.

Classification: given the context and a set of possible classifications for a particular piece of anatomy or pathology, the task of the radiologist is to determine whether the evidence meets the criteria for one of the set of possible classifications.

Measurement: the radiologist is required to measure a piece of anatomy or pathology, e.g. to estimate the volume or greatest dimension of a tumour.

The notion of task employed here is closely related to the idea of generic tasks developed by Chandrasekaran [3]. Each of the three tasks is defined in terms of a set of abstract rules defining the process used in the task, together with sets of facts representing the knowledge employed in the task. The representation of tasks is sufficiently abstract to be applicable across a range of image interpretation problems. The task specifications also make use of the notion of a generic sub-task, with component elements being shared between the three tasks.

4. Extended decision procedure

We propose a set of rules which form a model of the process of decision-making in image interpretation. The model includes rules specifying the three generic image interpretation tasks which provide the evidence used in making decisions. The aim of these rules is twofold: to provide a homogeneous representation of the different decisions and to control the construction of information from the various knowledge sources. These two aims correspond to the declarative and procedural interpretations of the rules. All the logical rules describing the decision-making process are given in Appendix A. The first three rules are an adaptation of those used in the Fox et al. symbolic decision procedure, and may be stated informally.

(1) the candidates to be suggested include every item in the knowledge base which is linked to the focus (the initial dilemma the decision-maker faces) by one of the appropriate proposal criteria for this kind of decision

Returning to the example depicted in Fig. 2, if the decision is diagnosis, the focus will be the patient's problem, the criteria for the proposal of candidates will be that they are potential causes of the problem. So, if the problem is 'breast lump' and the knowledge base records that 'causes of breast lump include breast cancer', then 'breast cancer' will be a suggested diagnostic candidate.

(2) the possible arguments relating to each candidate include every item in the knowledge base which is linked to that candidate by one of the appropriate criteria for this kind of decision

In diagnostic decisions the appropriate criteria for use in constructing arguments are signs and symptoms. So, if the knowledge base records that 'microcalcifications are a sign of breast cancer', then this is a possible argument in favour of 'breast cancer'.
(3) the decision support consists of all of the evidence for each of the findings used in arguments proposed for and against every candidate suggested from the specified focus.

So, if evidence of microcalcifications is found, then that evidence will form part of the information to be presented to the user in this case, together with the evidence found for the other signs and symptoms of breast cancer, and the signs and symptoms of the other possible causes of the breast lump.

We require a set of rules which characterise the three generic image interpretation tasks described in the previous section; rules which can be used in an extended decision procedure automatically to obtain evidence from images. Consider first how the detection task might be represented.

A symbolic model which controls the application of image processing operators to detect certain findings must include a representation of:

- how a finding appears in image data;
- which image processing operator is required to identify the feature in the image data; and
- how the output from the image processing operator is to be interpreted as evidence.

The image processing operation will return a value indicating the strength of the match between the image data and the representation of the finding and also a representation of where in the image the match was found. So we have a rule stating that:

(4) the evidence for each argument may include the value returned by a detector applied to the image to detect a feature which depicts the required finding

The key difference between the detection task on the one hand and the measurement and classification tasks on the other is that in the classification and measurement tasks a representation of at least part of the relevant anatomy has to be constructed: if you are to measure or classify something, then you must first have detected it. We require a model of the anatomy which lists the structures which must be detected before a particular classification or measurement decision can be taken, we also require information about how the structures are depicted in the image and which image processing operations can be used to detect the depictions. This permits the required detectors to be applied to the image and results in what we term an ‘interpretation’ of the image. Neither the model of anatomy nor the resulting interpretation need to be complete; they only represent what is required for the particular task.

In the case of the classification task, we also require facts relating the findings in the knowledge base to the model and a matching process which ascertains if the interpretation is suggestive of the presence of the finding.

(5) the evidence for each argument may include the result of matching the features depicting a finding against the interpretation of an image

The rule for measurement is analogous except that the finding is defined in terms of a measure and this measure is applied to the interpretation of the image.

(6) the evidence for each argument may include the result of measuring a component of the interpretation of an image
Another rule allows information entered by the radiologist onto the patient record to be used as evidence.

The extended decision procedure, therefore, consists of elements from the original decision procedure:
- a set of logical rules describing the process of decision structuring and decision making;
- a set of facts about different kinds of decision;
- a set of facts describing the domain in which the decision is to be made; and
- a set of facts describing what is known about the particular case augmented with:
  - a set of logical rules describing the generic image interpretation tasks;
  - a set of facts listing the structures to be identified in specific image interpretation tasks;
  - a set of facts describing how findings and other relevant structures are depicted in medical images; and
  - a set of facts describing how image processing operations are used to detect certain kinds of depiction.

5. Supporting image interpretation tasks

In this section we give examples of how the extended decision procedure outlined above is used to control the application of image processing in the presentation of decision support for three decisions, providing examples of detection, classification and measurement tasks.

5.1. The detection of microcalcifications

A great deal of research in the processing of medical images has been directed at the problem of detecting microcalcifications on mammograms. The standard approach to this problem is a two-stage process in which the image is first segmented to identify regions which are likely to contain microcalcifications, and then measured in various ways to allow a classification which will sort true from false positives. A recent workshop on digital mammography included seven papers on the topic [2,4,9,15,19,23,30]. Kegelmeyer [9] presents a method which brings together many different approaches taken with this paradigm and employs six different segmentation algorithms and measures 11 different features. In most of these papers there is a degree of consensus about how microcalcifications are depicted: as small areas of high image intensity or of high contrast with the surrounding region. Some authors analyse images in the spatial frequency domain and the depiction of microcalcifications is taken to be a range of high frequency components (e.g. [2]).

Recall the rule which described the detection task:

(7) the evidence for each argument may include the value returned by a detector applied to the image to detect a feature which depicts the required finding
To apply this rule to the detection of microcalcifications, for example in deciding whether or not to refer from screening, we must represent the way microcalcifications are depicted in image data. We do this using a list of the photometric properties of an image region which could correspond to a microcalcification.

(8) microcalcifications are depicted as small regions of high relative density

We require a detector which is specialised for small regions of high intensity. The segmentor which performed best in Kegelmeyer's study [9] is called the 'outlier' method, so we must represent the fact that:

(9) outlier is a detector for small regions of high relative density

The definition of the 'outlier' detector is given by Kegelmeyer as:

'A local window \( w \) around every point \( p \) is considered. If the grey-level of \( p \) is greater than a threshold defined as the mean of \( w \) plus three times the standard deviation of \( w \), the point is considered to be extreme. Extreme points are grouped into segmented calcifications on a 4-connected basis'

The application of the 'outlier' operator to the image is performed by applying a function which returns the regions of the image identified by the outlier detector. The outlier operator comprises instances of two generic classes of image processing operation. In the first a window is moved across an image and an output value calculated for the point at the centre of the window, in the second a binary image is converted into a list of regions corresponding to microcalcifications. The first operation requires three parameters: the window size, the statistics to be calculated for the window (the value at the centre of the window, the mean and standard deviation) and the output rule (if the value at the centre is greater than the mean plus three times the standard deviation the output is one, otherwise it is zero). The parameters for the second operation specify the class of pixels to consider (those with value one) and a size threshold (we used a threshold such that regions of fewer than 8 pixels are ignored).

(10) the regions identified by outlier are those returned by applying the region finder operator, with a threshold of 8 to the image created by moving a 32-pixel window over the image, computing the moments and applying output rule 1 at each stage. Output rule 1 is that if the value at the centre is greater than the mean plus three times the standard deviation the output is one, otherwise it is zero

Our implementation of this operator, when called with a 32 x 32 pixel window and a size threshold of 8 pixels, was sufficient to identify some microcalcifications in 12 out of 15 clusters (with only one false positive) on 512 x 512 pixel sections, such as those in Fig. 3, taken from images in the Mammographic Image Analysis Society's digital mammogram database [24], identifying 84 microcalcifications. This result is adequate as a demonstration of a detection task, and allows a classification task to be implemented: the classification of detected microcalcifications as benign or malignant.
5.2. The classification of microcalcifications

Microcalcifications, or apparent microcalcifications, are caused by a variety of processes, some are malignant, more are benign and a number are merely artifactual. [1,12,21,25] are among the authors describing the typical presentations of microcalcifications in each of these categories. Fig. 4 illustrates one commonly used scheme for the classification of microcalcifications. In a number of recent papers

Fig. 3. A fragment of a mammogram (top) showing a cluster of microcalcifications and (bottom) the regions identified by the outlier operator.
Fig. 4. There are a number of different systems for the classification of microcalcifications. One popular system is that devised by le Gal (see [5]) which groups microcalcifications into five different classes on the basis of their shape. Each class is associated with a different probability of malignancy.

authors have turned their attention to the problem of characterising microcalcifications. We have found five sets of authors who have published papers on the use of image analysis to distinguish benign from malignant microcalcifications [4,13,15,20,22] and one who uses similar ideas to distinguish comedo from non-comedo ductal carcinoma in situ [18]. We wish to employ some of the measures developed by these authors to provide information with a knowledge base which captures the information given in the above references.

Recall the rule from the decision procedure which describes the classification task.

(5) the evidence for each argument may include the result of matching the features depicting a finding against the interpretation of an image

First we require a representation of the model to be used in the classification task. The model must record the structures which have to be identified before we can perform the classification. Interpreting the image according to the model is a matter of identifying the image regions which correspond to the structures listed in the model. This involves a sequence of tasks, the sequence is analogous to the detection task, for each structure: the relevant depiction is first identified and then used to select an appropriate detector which can be applied to the image. The result of the interpretation process is a list of image regions associated with each of the structures in the model. This interpretation process, a sub-task of the classification and measurement tasks, is described in the following rule.

(11) the interpretation of an image according to a model is the list of regions identified by detectors which respond to the depictions of the anatomical features listed in the model

Our knowledge base refers to 11 different properties which may be used to describe microcalcifications; properties such as shape, distribution, location and size. However, the only property which refers to structures other than the microcalcifications or their clusters themselves is location. Possible locations referred to in the knowledge base include ‘close to nipple’, ‘inside fibroadenoma’ and ‘around a fibroadenoma’. The model therefore lists the nipple, microcalcifications, microcalcification clusters and fibroadenoma as items to be identified. The following is the interpretation required for the classification of microcalcifications.
to classify microcalcifications we must identify, the microcalcifications, microcalcification clusters and the surrounding normal tissue and significant landmarks such as the nipple and any benign tumour. This list of regions is then matched with the depiction of the finding, so if the required finding is that the microcalcifications are linear and the depiction of linear shape is the area to perimeter ratio, a rule which tests to see if the regions identified as microcalcifications have a high area to perimeter ratio is applied. Therefore, the following rules are required:

13. round shape is depicted as a high ratio of area to perimeter
14. the circularity operator classifies levels of area to perimeter ratio
15. if a region is classified using an operator which responds to a finding then the image containing that region matches that finding

5.3. The measurement of tissue density

One of the properties we wish to measure is the density of normal tissue in the mammogram. There are a number of reasons for being interested in this property: in order to be able to identify asymmetries [14], because denser breasts are harder to read and may require a different interpretative protocol [8] and also because density may be related to risk [17]. In an earlier paper [28] we presented a method for measuring the density of normal tissue in the breast. This method involves first locating a region of interest above and behind the nipple, as shown in Fig. 5, where, if the breast is dense, dense tissue will normally be found and second measuring the asymmetry of grey level histograms in non-overlapping 16 x 16 pixel windows within this region.

Fig. 5. The method used in the measurement of tissue of density. Thresholding is used to give a rough estimate of the breast outline and then an automated procedure is used to identify a region of interest behind the nipple. The measure, based on the asymmetry of grey-level histograms is applied in 16 x 16 tiles over the region of interest.
Recall the rule from the decision procedure which described the measurement task:

(6) the evidence for each argument may include the result of measuring a component of the interpretation of an image

The model required in this task distinguishes the breast region from the background. The finding is depicted as the ratio of lighter to dark pixels and measured using an operator which constructs histograms of small regions within the breast area, measures the asymmetry or skew of the histograms and takes the mean of the skew values. We require facts stating the model:

(16) to assess risk we must identify a region within the breast

recording how the regions in the model are depicted:

(17) a region within the breast is depicted as foreground

and identifying detectors for those depictions:

(18) the thresholding operator identifies the foreground

Similarly we must represent how 'tissue density' is depicted in the region of interest and how that depiction can be measured.

(19) tissue density is depicted as asymmetry in the grey-level histogram

Two image processing procedures are applied. First a thresholding operation is applied in the interpretation of the image according to the model. Secondly the skewness operator is applied to measure the tissue density in the region identified in the interpretation. The extended decision procedure includes a rule relating the evidence obtained to the original problem.

(20) if an image containing a region is measured using an operator then the returned value is a measure of the image

5.4. The prototype decision aid

We have implemented a prototype radiologist’s workstation, shown in Fig. 6, to support the management of patients referred from the UK’s national breast screening programme which provides all the functionality described in the preceding sections. It contains a knowledge base of facts which consists of all the statements about the appearance of mammographic abnormalities contained in [1,12,21,25], expressed in terms closely following those recommended in [16], and in addition includes a symbolic record of the protocol followed for the referral of patients from the UK’s national screening programme.

The extended decision procedure is implemented as a logic program in Prolog and the image processing operators described above are implemented in C and called from Prolog. The design, shown in Fig. 7, can be considered as a grid in which the columns are the different information types and the rows are the different functional elements. Thus one row, the user interface, consists of a set of objects each of which displays information from a different knowledge source, and provides functions to support appropriate interactions. These objects are implemented using a Prolog interface to the Motif windowing environment. The next row consists of the various knowledge sources. The knowledge is stored in sets of files and accessed by Prolog programs which simulate the action of a PACS system,
a hospital information system and so on. The final row contains the programs which carry out the various information processing tasks.

More details of the architecture are provided in [27]. The prototype is designed to be used in conjunction with digitised images from the MIAS database: a set of digitised mammograms widely used in the research community [24]. The mammograms are digitised to a spatial resolution of 50 μm pixel edge with a scanning densitometer with a linear response in the optical density range 0.0–3.2.

6. Discussion

The purpose of this work is to solve the theoretical problems associated with the provision of decision support based on information obtained from two distinct knowledge sources and represented in radically different ways: as digital images and as symbolic knowledge. In order to demonstrate the value of our approach it will ultimately be necessary to engineer a clinical prototype which can be installed in a radiology department so that its contribution to improving medical decision-making can be assessed. The many practical problems associated with such a study are not addressed in this paper. We have, however, described a framework which we believe may provide the basis for such a system and the practicality of our approach has been demonstrated by the implementation of a demonstrator applica-
tion in the domain of X-ray mammography and the details of relevant aspects of its implementation are given here. The design is intended to be generic and a prototype system has been developed to support staging and assessment decisions based on the use of CT in the management of childhood abdominal tumours.

In the introduction we listed a number of different kinds of knowledge source which could be used to assist in radiological decision-making. Two types of information which we have not considered so far in our work are the statistics used in Bayesian decision models and databases of interpreted images.

Authors such as [11] have argued for the application of quantitative models to decision-making in radiology. In cases where the required data are available we would want to make use of them. In the current prototype such information is not used. However, the symbolic decision procedure does allow quantitative information to be presented to the user as an important component of the decision support. Our use of the procedure is to organise the presentation of decision support information in the form of evidence for arguments, no facility is provided for combining numbers associated with different arguments, or with different pieces of evidence for an argument. This reflects an important area of remaining research: the integration of measures of uncertainty associated with the application of image processing to digital images. Uncertainty arises through the fallibility of the image processing, the imprecision in the radiological descriptions it seeks to capture, through the uncertainties of the image-forming process and through the probabilistic association between radiological signs and the underlying disease processes. Further difficulties arise from a consideration of how uncertain information from

Fig. 7. The architecture of the prototype. The rounded boxes represent the different elements of the user interface. The drums in the second row represent the different knowledge sources while the boxes in the bottom row represent the programs which manipulate the information in the knowledge sources. The arrows in the above diagram show how information flows through the system when a patient summary and images are displayed, a radiologist's report is entered and image processing and medical knowledge are combined by the decision procedure to provide decision support.
different imaging modalities, or even different areas of a single image, should be combined.

We hope to address these issues in our future work and also hope to consider how some of the decision support functions we already provide could be augmented with the inclusion of images from a database of stored images covering the range of possible interpretation problems. For example, the decision support provided for the classification of microcalcifications could include the presentation of archive images in which the measured shape of the microcalcifications matches that of the mammogram being considered.

Although we believe our work to be of quite general applicability, the prototype described in this paper was designed specifically to support the use of mammography in the handling of patients referred from the UK breast cancer screening programme. The screening programme has been the focus for much work in medical image processing. We believe the interpretation of screening mammograms by radiologists is performed so rapidly, and involves such a high throughput of images that the potential for decision support is relatively limited. However patients are referred from screening for further investigation and it is at this stage that we expect the use of a system such as ours to be both practical and important. The volume of patients seen means that any improvement in the capacity of radiologists to select an appropriate course of action, to identify benign lesions or to assess risk, must have enormous potential for the improvement of patient care.

7. Conclusions

Useful aids for clinical decision making which incorporate image processing are now a practical possibility, but a range of intellectual problems must be solved before this new technology can be applied in practice. One group of these problems may usefully be addressed by the decision support theorist. We present a framework which allows information obtained from image processing to be incorporated into a knowledge-based decision support tool. This framework allows for the effective presentation of relevant information and provides a useful context within which to incorporate image processing. Areas requiring future work include the representation of uncertain information obtained from the image to allow the computation of an overall certainty in a particular hypothesis or decision candidate. The integration of information obtained from different sources and from different images, or even from different locations within the same image, will provide a challenge for future work.

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Appendix A

We present here the complete set of the rules mentioned above. The syntax used here is adopted for the purpose of this exposition only and is a rewriting of the Prolog program used. Variable names begin with an upper case letter.

(1) the candidates to be suggested include every item in the knowledge base which is linked to the focus (the initial dilemma the decision-maker faces) by one of the appropriate proposal criteria for this kind of decision

\[
\text{If} \quad \text{proposal_criteria}(\text{Decision, Criteria}) \\
\text{and} \quad \text{fact}(\text{Criteria, Focus, Candidate}) \\
\text{then} \quad \text{proposed_candidates}(\text{Decision, Focus, Candidate})
\]

(2) the possible arguments (with positive or negative force) relating to each candidate include every item in the knowledge base which is linked to a candidate by one of the appropriate criteria for this kind of decision

\[
\text{If} \quad \text{arguments}(\text{Decision, Force, ArgumentType}) \\
\text{and} \quad \text{fact}(\text{ArgumentType, Candidate, Finding}) \\
\text{then} \quad \text{argument_for_candidate}(\text{Decision, Candidate, Force, Finding})
\]

(3) the decision support (the complete set of information provided by the system) consists of all of the evidence for each of the findings used in arguments proposed for and against every candidate suggested from the specified focus

\[
\text{If} \quad \text{proposed_candidates}(\text{Decision, Focus, Candidate}) \\
\text{and} \quad \text{argument_for_candidate}(\text{Decision, Candidate, Force, Finding}) \\
\text{and} \quad \text{evidence_for_argument}(\text{Decision, Patient, Finding, Evidence}) \\
\text{then} \quad \text{decision_support}(\text{Decision, Patient, Focus, Candidate, Force, Finding, Evidence})
\]

(4) the evidence for each argument may include the value returned by a detector applied to the image to detect a feature which depicts the required finding
/* detection */

\[
\text{If} \quad \text{patient_has_images}(\text{Patient, ImageType, Image}) \\
\text{and} \quad \text{depictions}(\text{Finding, ImageType, Feature}) \\
\text{and} \quad \text{detector}(\text{Feature, ImageType, Detector}) \\
\text{and} \quad \text{detector_applied_to_image}(\text{Images, Detector, Region, Value}) \\
\text{then} \quad \text{evidence_for_argument}(\text{Decision, Patient, Finding, [Detector, Region, Value]})
\]
(5) the evidence for each argument may include the result of matching the features depicting a finding against the interpretation of an image
/* classification */

\[
\begin{align*}
\text{If} & \quad \text{patient\_has\_images(Patient, ImageType, Images)} \\
\text{and} & \quad \text{model(Decision, ImageType, Model)} \\
\text{and} & \quad \text{interpretation(Images, Model, Interpretation)} \\
\text{and} & \quad \text{depictions(Finding, ImageType, FeatureSet)} \\
\text{and} & \quad \text{depiction\_matches\_interpretation(Images, Interpretation, FeatureSet, Value)} \\
\text{then} & \quad \text{evidence\_for\_argument(Decision, Patient, Finding, [FeatureSet, Interpretation, Value])}
\end{align*}
\]

(6) the evidence for each argument may include the result of measuring a component of the interpretation of an image
/* measurement */

\[
\begin{align*}
\text{If} & \quad \text{patient\_has\_images(Patient, ImageType, Images)} \\
\text{and} & \quad \text{model(Decision, ImageType, Model)} \\
\text{and} & \quad \text{interpretation(Images, Model, Interpretation)} \\
\text{and} & \quad \text{depictions(Finding, ImageType, Measure)} \\
\text{and} & \quad \text{measure(Images, Interpretation, Measure, Value)} \\
\text{then} & \quad \text{evidence\_for\_argument(Decision, Patient, Finding, [Measure, Interpretation, Value])}
\end{align*}
\]

(7) the evidence for each argument may include items recorded by a radiologist /* previous interpretation */

\[
\begin{align*}
\text{If} & \quad \text{patient\_has\_images(Patient, Images)} \\
\text{and} & \quad \text{radiologists\_interpretation(Images, Finding, Region, Confidence)} \\
\text{then} & \quad \text{evidence\_for\_argument(\_, Patient, Finding, [radiologist, Region, Confidence])}
\end{align*}
\]

(8) microcalcifications are depicted as small regions of high relative density
depictions(microcalcifications, mammograms, region([small, high\_relative\_intensity]).

(9) outlier is a detector for small regions of high relative density

\[
\begin{align*}
\text{If} & \quad \text{includes(Properties, small)} \\
\text{and} & \quad \text{includes(Properties, high\_relative\_intensity)} \\
\text{then} & \quad \text{detector(region(Properties), mammograms, outlier)}
\end{align*}
\]

(10) the regions identified by outlier are those returned by applying the region finder operator, with a threshold of 8 to the image created by moving a 32 pixel window over the image, computing the moments and applying output rule 1 at each stage
If
and
then

detector_applied_to_image(Images, outlier, Region, Value)

(11) the interpretation of an image according to a model is the list of regions identified by detectors which respond to the depictions of the anatomical features listed in the model

If
and
and
and
then

first_item_of_list(FirstItem, RemainingItems, List)
interpretation_of_item(Images, FirstItem, Region)
interpretation_of_item(Images, RemainingItems, RemainingRegions)
first_item_of_list(Region, RemainingRegions, Regions)
interpretation(images, List, Regions)

If
and
and
then

depictions(Item, ImageType, Feature)
detector(Feature, ImageType, Detector)
detector_applied_to_image(Images, Detector, Region, Value)
interpretation_of_item(Images, Item, Region)

(12) to classify microcalcifications we must identity, the microcalcifications the microcalcification cluster and the surrounding normal tissue and significant landmarks such as the nipple and any benign tumour
model(classification_of_microcalcifications, mammograms, [breast tissue, microcalcifications, nipple, fibroadenoma]).

(13) round shape is depicted as a high ratio of area to perimeter
depictions(linear_microcalcifications, mammograms, ratio(area, perimeter, low))

(14) the circularity operator classifies levels of area to perimeter ratio
measure_of_property(circularity, ratio(area, perimeter, low))

(15) if a region is classified using an operator which responds to a finding then the image containing that region matches that finding
If
and
and
then

includes(Interpretation, Region)
measure_of_property(Measure, Property)
apply_measure(Images, Property, Region, Value).
depiction_matches_interpretation(Images, Interpretation, Property, Value)

(16) to assess risk we must identify a region within the breast
model(assessment_of_risk, mammograms, [breast_region]).

(17) a region within the breast is depicted as foreground
depictions(breast_region, mammograms, foreground).

(18) the thresholding operator identifies the foreground
If
and
then
includes(Properties, small)
includes(Properties, high_relative_intensity)
detector(region(Properties), mammograms, outlier)
(19) tissue density is depicted as asymmetry in the grey-level histogram depictions (tissue density, mammograms, grey level asymmetry).

(20) if an image containing a region is measured using an operator then the returned value is a measure of the image

If includes(Interpretation, Region)
and apply_measure(Images, Measure, Region, Value)
then measure(Images, Interpretation, Measure, Value)

References


