Cognitive Measures for Visual Concept Teaching with Intelligent Tutoring Systems

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Abstract: This article reports on the application of general cognitive measures to describe and order the knowledge base of radiological images, aimed at the teaching of visual concepts through ITSs. The methodology adopted embraces the authoring process by means of software tools that aid the creation of appropriate teaching sequences which tend to cause a reduction in a student's learning time and to allow the use of various pedagogic strategies. We also present a case study to illustrate the use of cognitive measures in the teaching of brain lesions through CT scans of the head.

Key-words: Authoring tools, Visual concepts, Radiological expertise.

List of topics: Authoring shells and tools, Cognitive modelling, Knowledge elicitation.

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1 Introduction

The expertise acquisition in medical Radiology may be considered more of a training than a teaching scheme. This is due to the fact that the novice residents are medical doctors who already know the radiology principles but they're not able to build mental representations about radiological problems and use their knowledge to solve those problems (Lesgold, 1984).

This work consists of a conceptual definition of cognitive measures to order a set of images of an Intelligent Tutoring System (ITS) and on the implementation of software tools based on these measures. The class of ITS treated in this work is driven to the teaching of visual concepts, especially those for medical Radiology. The goal is to enable the automation of the choice of subsequent images to be presented to the learner, simulating the human teacher experience and making use of many possible pedagogic strategies.

In a traditional or computer-based teaching session, after the discussion on a case is carried out by the teacher, another case is chosen and introduced to continue the session. One problem is how this following case is chosen. In real classes, teachers use their compiled knowledge and experience. This is due to the fact that the real teachers don't know exactly what are the criteria they use to plan the order of example cases. Existing ITS tend to use fixed orders, previously established, all of them strongly based on the frequency of occurrence of an exemplar in the real world. Also, these ITS are domain-specific systems, totally ignoring the domain-general authoring and interpretation dimensions.

2 Computer-based tools for visual concepts

The Radiology Tutor, developed by Sharples and Du Boulay (Sharples and du Boulay, 1988; Sharples, 1989), is a medical radiology teaching system. It was the first system that uses artificial intelligent techniques. It was built to develop expertise on medical X-ray images based diagnosis. The MR-Tutor (Sharples et al., 1997) differs from the Radiology Tutor teaching line in the socio-cognitive view. It was built taking account of social aspects of the trainees like their learning preferences.

The RUI system (Representations for Understanding Images) (Direne, 1993) is a domain-general environment for the design and tutorial interpretation of visual concepts teaching ITS material. It's basically an environment where an expert radiologist, assisted by a knowledge engineer, is able to input the ITS knowledge and easily modify it without the need of conventional programming tools such as compilers.

An ITS that allows the teaching sessions to be easily created or edited, is called an authoring environment. The language used to make this creation or edition is called authoring language. Because of that, authoring environments compose an important family in the computer-based instruction area. Among some relevant contribution on authoring environments, such as the Courseware Development Templates (O'Shea et al., 1984), the COCA (Major and Reichgelt, 1991) and the DACTN (Murray and Woolf, 1992), the RUI (Direne, 1993) system is adopted as the basis for this work because it's designed specifically for visual concept teaching. In a typical teaching session of ITSs designed with RUI, an example is discussed with the learner and the diagnostics is build in a progressive way. An image database supplies the teaching sessions with medical cases. This database is composed of pixel files and symbolic image descriptions, each one associated with a class of abnormality. before this research project, the RUI was only able to adapt the dialog to track a learner's deficiency within the scope of a single image but, at present, it's also able to select ordered sets of examples to be presented.

3 Cognitive measures

Cognitive measures are a way to help expert Radiologists to externalise some of the meta-knowledge about the examples of an ITS for visual concepts. Also, they are the main link between an ITS domain model and its tutoring model to deal with issues of complexity of the diagnosis.

There are some fundamental capacities of medical Radiology expertise that have been described in detail (Lesgold, 1984). The most significant ones are: (1) 2D-3D mapping, (2) differential diagnosis, (3) proportion-based trained eye, (4) and technical vocabulary.

In order to find out a measure that cognitively quantifies an example, it's necessary to analyse how this example will contribute to the learning process. The cognitive load of an example can be defined as the capacity that an example has to train the diagnostic abilities of the learner. The cognitive load of an example can be decomposed in some components. Each one of those components will measure one of the 4 types of capacity referred above that contribute to the learning process.

In medical radiology there are already some image-related measures. These measures are frequency, salience and reliability. Frequency is defined as the number of occurrences of similar to the example images in the set of the images of the example's abnormality class. Salience measures the qualitative value of the sum of the main image features for main diagnosis that are highly visible. Reliability measures how much an example has in terms of common features to the other examples of the same class of abnormality. This indicates how it is easy to give a diagnosis to the example, which means the image diagnosticity.

The measures briefly described above are appropriate for generic visual concept teaching (Sharples, 1991). Therefore they can be used either in medical radiology as well as in geology or botany. An image presented to a learner also contribute to the acquisition of the expert radiologist stereotype features. Each image has certain features that contributes to the acquisition of certain expert stereotype features more than others. This leads to define specific measures of image features for medical radiology. These measures are defined from the stereotype of an expert radiologist and they are used to quantify the image's demand on each stereotype feature.

This demand can be measured for each expert stereotype features. Three of these features were chosen to represent three of the most significant cognitive dimensions in the Radiological diagnosis. Three-dimensional vision capacity represents the visual component. Differential diagnosis represents the component of the mental schema showing that the trainee already solves problems. The verbal expression component is represented by technical synonyms.

The three-dimensional vision capacity is defined as how much the image demands from the learner to infer a third dimension from a bi-dimensional image. The differential diagnosis capacity quantifies the image in how much it demands from the learner to search for little details in order to classify it as an image of one class of abnormality instead of another. technical synonyms is defined as the capacity of the learner in using more specific terms in the diagnostic instead of more generic ones.

The cognitive load of an image is computed as a composition of its cognitive measures. It is calculated using the following formula:

$$G = \frac{\alpha frequ + \beta sal + \gamma conf + \delta vtd + \theta ddif + \omega stec}{\alpha + \beta + \gamma + \delta + \theta + \omega}$$

where: frequ, sal, conf, vtd, ddif and stec are the values for frequency, salience, reliability, three-dimensional vision capacity, differential diagnosis capacity and Technical synonyms, and α, β, γ, δ, θ and ω are the weights associated with each cognitive measure, given by the expert.

Each measure has a different weight in the cognitive load composition. An example of this fact is the frequency measure that contributes with a high weight and technical synonyms with a low weight. The weight of each measure is obtained by information given by expert radiologists. Frequency, salience and reliability have negative weights because they are inversely proportional to the load. The other measures have positive values.

4 Case study

In order to illustrate the use of the cognitive measures in medical radiology visual concepts teaching, a study was done with an expert radiologist and a set of radiological images. The goals of this study were the followings: (1)to find a more interesting form to allow the expert himself to cognitively describe those images, (2)to empirically determine the weigh of each cognitive measure on the result of the cognitive load, (3)to evaluate the relevance of each measure and to validate the usefulness of the cognitive load in the ordering of image sets to be presented to the learner.

This study has been carried out in collaboration with the Department of Radiology in the local University hospital. They maintain a large stock of radiological images of different kinds of abnormality. One of the most significant parts of this collection is the brain tumor CT-scans collection, which was chosen as the object of this study.

This study has followed four main stages. The first one was the presentation of the cognitive measures to the expert and a discussion about their possible relevance to a computer-based teaching system.

The second stage was the process of developing and validating a form to acquire the cognitive measures from an image. The choice of using a form is due to the fact that this way of data acquisition is easy to implement on a computer and also it's widely used in hospitals.

Expert's classification	
types of cases	images numbers
easy cases	6, 8, 9, 12, 13, 3, 2, 19, 17, 18 and 22
medium cases	1, 5, 7, 20, 15
difficult cases	14, 16, 4, 10, 11 and 21
System classification	
18, 22, 17, 13, 3, 12, 19, 8, 9, 1, 20, 15, 7, 6, 5, 2, 4, 10, 14, 21 and 16	

Table 1: Cognitive classification of the case study images

Twenty two CT-scans brain tumor were chosen for the cognitive data acquisition. The experts have attributed values to the cognitive measures for the whole image and for features of the lesion. At these stage were also acquired from the expert, possible weights for the cognitive measures to be used on the calculation of the cognitive load.

During the cognitive data elicitation phase, the expert has classified the images by estimating the cognitive load of each image feature. The values were input in the knowledge base through an implemented software tool which will be described in Section 4.

Despite some differences found between the image classification performed by the expert and the ones computed by the system, the results of such classification are very similar. To substantiate this assumption, if the resulting ordered set computed by the system is split in three sets of images, the content of the sets will roughly match the content the expert's classification, also split in three sets that range from easy to difficult cases (see Table 1). This indicates that the cognitive load is an adequate measure to represent cognitive knowledge about the images.

5 SEQUENCE: an authoring tool

The goal of this tool is to facilitate the use of the values of the cognitive parameters by the expert author. This is to support the structuring of a sequence of learning sessions that will be presented to the learners.

Sequence allows an ITS built using the RUI system to include long-term control over the various learning sessions. In its early version, RUI allowed tutorial control only within the scope of a single image. The long-term choice of the examples to be presented to the learners can also be made by a human teacher or by the learner himself. The Sequence tool allows the ITS author to determine which and how many will be the examples presented to the learners, either directly (by choosing specific example images) or indirectly (by setting parameters to allow the system to make this choice). According to previous work, appropriate choices of case difficulty along the time even tends to keep the learner in a high motivational state (Del Soldato and Du Boulay, 1995), where some of the benefits are a decrease in learning and/or teaching times.

The authoring process using the Sequence tool is carried out in two levels. The first one is the course level. In this level the author will set the learning session format. He will set the number of images of the session, which will be these images, the presentation

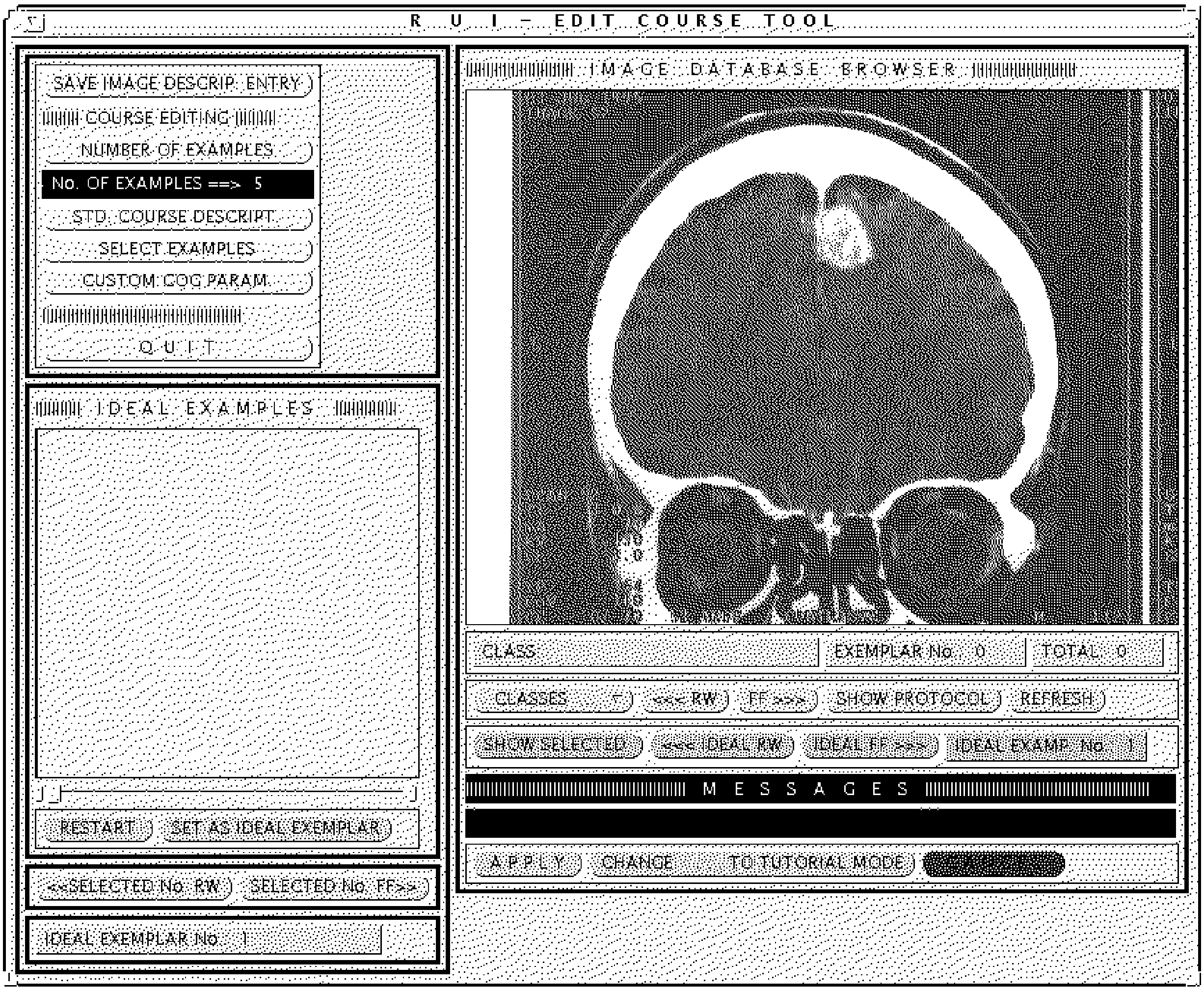

Figure 1: Sequence main window

order of these images and other images presentation control parameters for the course.

The second level is the cognitive image description. It is a complement of the production level of RUI (Direne, 1993). The main function in this level is to make it possible for the ITS author to represent and store the knowledge about the cognitive capacity of each exemplar together with the medical knowledge description of the case, elicited using RUI. It is important to remark that the cognitive measures are also part of the image description.

The link between the course level and the cognitive image description level is made by the cognitive values. These values serve as a feedback for the author to know the quantitative cognitive load of each example. With this information the author can chose or parametrise an automatic choice of the images that will be presented to the learner.

6 Conclusion

In this work, cognitive measures are described and used to order a knowledge base of example images so that the tutorial model of an ITS can easily modify the order of image presentation in the long-term teaching tasks. These measures quantify the image potential to exercise specific learner capacities that must be developed for the learner to become an expert. They also measure and computationally represent the cognitive load of those images so that they can ben quantified with less subjective values of how difficult the Radiological diagnosis is. Also, these measures aim to individualise the teaching process. They allowing an expansion of pedagogical strategies that fits better to the learner and permit changes in order to correct eventual long-term mistakes.

The main contribution of this work has been an authoring model for visual concept knowledge. This is achieved through a more adequated choice of examples to be presented to the learner, shortening the gap between the tutorial model and the domain model of an ITS. A case study has been carried out to apply the referred cognitive measures in an attempt to quantify the cognitive load of image diagnosis.

As a future work, we propose the conception and implementation of a complete, domain-general model of ITS tutorial interpretation of visual concepts. These will include both tactical (short-term) or the strategical (long-term) feedback features to the learner, integrated in the intelligent teaching shell of the RUI system. We expect that such a domain-general model will not only incorporate the ordering effect of the cognitive measures but also give the ITS author a new dimension in terms of simulated teaching scenarios that go beyond the dialogue around a single Radiological case.

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