Anesthesiology deals with such complex social systems that it can span over an infinite number of states. Diagnesia, a prototype built to offer decision support to anesthetists continuously estimates the likelihood and unlikelihood of diagnoses during surgery, by applying arguments for and against the different diagnoses, and presents the most probable diagnoses to the anesthetist. In this paper, we present the usability aspects and/or design decisions pertaining the prototype.

1. Introduction

When patients go to the operating theatre for surgery, they need some sort of anesthesia in order not to feel conscious pain. This paper will focus on this type of anesthesia, referred to as general anesthesia. Anesthesia suppresses some vital functions of the patient. Kizito [2008] and Ballast [1992] discuss several effects of this. These include loss of water, blood loss, vasodilatation, suppression of autonomic nervous function, and so on. Since the patient is unconscious, unaware of pain, and immobile during the period he/she is anesthetized, he/she is unable to express him/herself. We thus have a specialist in the theatre responsible for the health of the patient during this time—the Anesthetist.

The specialist is able to monitor the state of the patient by use of monitoring devices. These devices continuously display the patient’s physiological data, which when coupled with registrations of certain events, medical history, and drug administration can be used to estimate the state/health of the patient. Such data may include, but is not limited to, blood pressure, heart rate, respiratory rate, oxygen saturation, and anesthetic concentration of gas mixture. When any of these values goes out of the normal range, the Anesthetist has to take appropriate action.

In [Kizito, 2008], we discussed in detail the states of the patient. We categorized them into three; familiar (to the anesthetist), urgent, and diagnosing states. In the familiar state, the Anesthetist knows the typical treatment to give the patient. The urgent state is unfamiliar but nevertheless, the Anesthetist needs to give some treatment even without knowing the cause of the problem. The diagnosing state is also unfamiliar but not urgent and thus can not be diagnosed like the familiar case. In this paper, we present approaches towards providing information in all these three dimensions.

Diagnesia, a prototype designed to offer decision support to the Anesthetist, continuously estimates the likelihood and unlikelihood of each of the diagnoses in its list, and presents such relevant information at such an abstract level that, this information
coupled with his expert knowledge, the Anesthetists decision making process can be facilitated [Kizito, 2008; Pott and Feber, 2005]. Physicians often refer to their clinical decision making process as more art than science, and suggest that while computers might be programmed to deal with the scientific, analytical aspect of their work, they will never be able to capture the “art” of a skilled clinician [Pople, 1992]. The decision support system can thus not do without the experts’ knowledge. This paper discusses the use of Information and Communication Technology (ICT) techniques to relay this kind of information and also discusses how such information is presented to the specialist. We shall also discuss the design decisions made in accordance with usability.

Using some defined indicators as inputs, Diagnesia builds a set of rules that are used to continuously estimate likelihood and unlikelihood of diagnoses in its set by computing corresponding evidence probabilities. Every diagnosis has a set of indicators and counter indicators, each with a certain strength/weight. The indicators are used to estimate the evidence probabilities [Kizito, 2008]. At any one point, the outcome of this computation is a paired set of probable diagnoses and corresponding estimated probabilities. This paper will not focus on how these probabilities are computed but rather on how the findings are relayed to the relevant personnel.

2. Usability Design Decisions

In this section, we look at a number of aspects considered when designing Diagnesia’s user interface. The user interface is an important aspect of the system. It is through this interface that the system keeps the user informed about what is going on through appropriate feedback within reasonable time. Diagnesia is designed in such a way that the information displayed can easily refresh every so often by setting a value of the refresh timer.

The system should speak the users’ language, with words, phrases and concepts familiar to the user, rather than system-oriented terms. It should follow real-world conventions, making information appear in a natural and logical order. The terms and/or abbreviations used to describe diagnoses, arguments, and the like, are those that anesthetists are familiar with, taken from literature of anesthesiology [Aitkenhead et al., 2001].

The user interface contains two major screens. An input screen (mainly for simulation and/or testing purposes) and the output screen (for Anesthetists use). This paper will focus on the output of the system thus the output screen. It is also very important that the information displayed on the interface is actually relevant to the anesthetist. The next sub-sections describe the approach used to ensure relevancy of the information displayed by the output screen of the decision support system (DSS).

2.1 Most probable diagnoses (the familiar state)

Previous research has attempted the use of approximation strategies in offering decision support to diagnosis [ten Teije and van Harmelen, 1996, 1997]. Diagnesia follows a similar approach by using estimated probability as a measure of the most likely diagnosis. The likelihood and unlikelihood of a diagnosis is estimated as a ratio of the total score
of all arguments (expected to contribute to the evidence) that are true to that of all those expected to make a contribution for the evidence in question (see Kizito [2008] for details).

When designing the way Diagnesia displays both the likelihood and unlikelihood, our intention is to make it easy for one to distinguish between the two. Although the likelihood may be superimposed on the screen more than the unlikelihood, the unlikelihood is also very important and should not be neglected. In collaboration with a usability class in the Department of Artificial Intelligence of the University of Groningen, we adopted a logarithmic scale, with a measure of time and evidence, as shown in Figure 1. This allows us to put more emphasis on the current state (far right) of the patient as well as keeping track of the historical states (towards the left). The orange shaded area shows the likelihood of the diagnosis at a given time, whereas the blue (later changed to green) line shows the unlikelihood.

Fig. 1. Indication of likelihood and unlikelihood of diagnosis

2.2 The urgent state

In [Kizito, 2008], we discussed some states of the patient. We noted that the state of the patient may be unfamiliar to the anesthetist and, in such cases, there is not enough time to investigate the cause of the problem. The anesthetist needs to give a treatment in order to bring back the patients state to normal. In this state, it is important for the anesthetist to have an idea of what category the problem is and the extent to which it is life threatening. Is it a Cardiovascular, Respiratory, or Anesthesia depth problem? If we have a problem in more that one of these categories, where do we have more urgency?

Approximation strategies are informed by particular properties of the domain knowledge [ten Teije and van Harmelen, 1997]. The work of Bravata et al. [2004] shows specificity as one of such properties that affect diagnostic closure when using approximation techniques. We thus attempt to provide some information in a more specific and precise manner. We consequently use three sets of icons to reflect the patient’s state along these three dimensions: the heart (for indicating problems with the cardiovascular system), lungs (for the respiratory system) and eye (for the depth of anesthesia). By moving the icon for a particular category to some direction, it should indicate more life threatening situations where as the withdrawal to the opposite direction should indicate more stable state. The icons may be in one of four positions; normal (not life threatening), low, intermediate, and high (life threatening).

Taking an example of the Anesthesia category, it is interesting to note that the system could easily come up with a scenario in which the patient has a low sleeping depth and at the same time a low awakening. This can be obtained in case the two arguments High MAC (argument for sleeping depth) and Low amplitude pulse oximeter (argument for awakening)
happen to be true at the same time. It is a contradiction because one is not expected to have an increasing depth of anesthesia and at the same time waking up! However, since it is a possible scenario according to the rules built into the system, a decision of handling this case has to be made. Considering the fact that it is more dangerous for a patient to wake up without the knowledge of the anesthetist than sleeping a bit more, it was decided that the awakening alarm overrides the one of sleeping depth. So, if such a scenario ever arose, the awakening icon will move to reflect the state of the patient along the dimension. We shall discuss more about these icons in 2.5.

2.3 Non Measurable (Observable) Variables

Diagnesia uses a number of variables to test the truth of the corresponding arguments. The likelihood of a diagnosis is then estimated depending on the number of arguments for the diagnosis that evaluate to true and their corresponding weights. In some instances, it is hardly possible to reach conclusive diagnostic closure as the system may require additional observation [Mcllraith and Reiter, 1992]. For example the system cannot tell whether or not the patient is sweating. These arguments are important and may be needed to confirm certain diagnoses. At the moment, we are unable to directly measure these variables. Perhaps it is possible to investigate the possibilities of measuring them but in the scope of our study the cost of this investigation may not be worthwhile. Some of them probably can be computed from some other information measured from the monitoring devices. Nevertheless, the system is designed in such a way that it is not hard to add more arguments for disorders.

Such arguments have further been categorized into three groups: one group can be observed, checked on the user interface, and considered in probability computations; another group cannot be considered when estimating probabilities but can be highlighted in the status bar of the user interface when there is suspicion that it should be observed; the last group is not considered at all by the DSS.

Checkable on the user interface: In this category, a checkbox has been provided on the input screen. For instance if the anesthetist realizes that the patient is sweating, he/she simply needs to check the box provided for sweating and the DSS will take it into account when estimating the probabilities of diagnoses. This method is not so user friendly and was limited to only two arguments (Mottled skin and Sweating) since one has to remember to uncheck such checkboxes when the observed action stops.

Alert message in status bar: As the number of observable arguments increased, the method described above could not be used anymore. Another mechanism was devised. A status bar was added at the bottom of the output screen of the system. When the diagnosis indicated by an argument is supported by any other measurable argument with a probability greater than 0 (zero) and qualifies to be among the probable diagnoses, then we can advise the anesthetist to check the observable arguments. We do this by putting some text in the status bar explaining what to observe and for what diagnosis. This text will disappear as long as the diagnosis in question loses the support. The text should slowly scroll to the left when it is too much to be accommodated in the available space of the status bar. A sample display of this feature will be presented in 2.5.
Other: The method described above can only work if the diagnosis indicated by the observable argument has at least one other measurable argument. Otherwise it will never get a chance of displaying its “help” information since it cannot raise any probability greater than zero. Such cases, where the only argument known for a diagnosis is an observable one, are not implemented in the system. For example, the system cannot know that there is a widening of the QRS complex on the ECG and since this is the only argument we have for hyponatraemia, the diagnosis (hyponatraemia) is not in the set of 36 catered for in Diagnesia.

On addition to the diagnosis affected by the Other category above, Diagnesia does not cater for hemorrhage. This is also due to the unease of measuring the disorder. Hemorrhage is a copious discharge of blood from the blood vessels. According to a textbook of anesthesia [Aitkenhead et al., 2001], blood loss can be estimated by weighing swabs, measuring the volume of blood in suction bottles and assessing the clinical response to fluid therapy. Estimation is always difficult where large volumes of irrigation fluid have been used.

2.4 Unavailable Measurements

Diagnesia is designed to be integrated with the current systems in order to automatically read the input values. However in normal cases, where there is no need for extra monitoring, the standard set of monitoring variables may be measured and are available. However, a variable may not be read because of a failure in the integration software, disconnection or damage in cables or any other computer and/or connection failures. In such cases, we think it is wise to assume that the variable in question is simply not being measured.

Because of this uncertainty of which variable is available for measurement, the system is designed in such a way that every variable may or may not be available at a certain point in time. When a variable is unavailable for measurement (irrespective of the cause), the DSS drops all arguments related to the variables from the set of arguments to be considered. We simply assume that we know nothing about it. In fact, we do not know if it is normal or out of range. If a diagnosis indicated by such a variable is supported by some probability high enough to qualify it among the probably diagnoses (despite the absence of at least one of its arguments), the DSS will show nothing about the corresponding argument for the unavailable variable.

This method affects the algorithm for the estimation of probabilities since the weights are assigned and thought about with the assumption that we have all the arguments contributing to the probability of the diagnosis. It should also be noted that this might make a certain diagnosis become single argument, which have their own challenges (not discussed in this paper) since they easily give rise to 100% evidence.

2.5 The User Interface

Figure 2 shows a complete snapshot of a sample output screen of Diagnesia. In the top left corner are the icons used to reflect the patient's state along the three dimensions: the heart, lungs, and eye as mentioned earlier in 2. The further the icon moves to the right the more critical the state of the patient. The previous state of the icon is
shown by a faded version of the icon and an arrow to show the trend. In order to provide more information along with the movement of the icon, the criticality of the situation has been coded with visual effects: the heart “breaks”, the lungs turn black, and the eye either opens (patient is waking up – not in picture) or one of two typical electroencephalogram (EEG) curves for deep anesthesia is superimposed on the closed eye icon. Clicking on any of the icons displays the production rules used to determine the state of the icon group in question.

**Fig. 2. Diagnesia user interface**

In the lower section of the screen, the system displays up to five most likely diagnoses (that might further explain the state of the patient). These diagnoses are initially arranged in order of the difference likelihood – unlikelihood however, when the system re-computes the probabilities and has to replace one or more of the currently displayed five diagnoses, the one with the smallest difference will be replaced first without re-ordering the diagnoses. This prevents movement of the graphs considering that one may be observing a particular graph. In addition, the name of the new entrant to the list is displayed in bold font to reflect the change.
In the top right corner of the screen is highlighted the first likely diagnosis however, the anesthetist may decide to instead observe another diagnosis by selecting its name from the drop-down list above the graph. This could be because the anesthetist chooses to observe the pattern of the likelihood for a certain diagnosis, which may not be displayed among the probable diagnoses. This can be relevant when the anesthetist expects or suspects something to happen because of his/her knowledge about the patient’s health condition, past experience, action taken by the surgeon, or any other factors that may cause the anesthetist’s suspicion. When this happens, the system does not override the selected diagnosis with any other until the anesthetist decides to (by selecting another one from the list). Furthermore, the category of the selected diagnosis is shown besides the select box. For **Hypervolemia** (in Figure 2), we have **Cardiovascular System**.

Yes, Diagnesia can suggest diagnoses with corresponding probabilities, but *if I really want to find out how it came to such a conclusion?* Anesthetists want to be aware of the situation as clear as possible. It is very important that the information supplied by the DSS does not conflict with the strategies of the anesthetist. It should therefore be possible for the system to display summarized and clear information that explains how it comes to the suggested conclusion. Consequently, we have the arguments for and arguments against that the system has used to approximate the current probabilities of the selected diagnosis. A checked box against the (counter) argument implies that the (counter) argument was found to be true.

**Color-coding:** We group all the diagnoses in four different categories namely cardiovascular, respiratory, anesthesia, and others. Each of these categories is assigned a color-code. That is to say, red for cardiovascular, blue for respiratory, brown for anesthesia, and black (default) for others. The names of the diagnoses against their corresponding graphs are printed in the respective color using this scheme. In Figure 2, we have a lot of red diagnoses thus a possible reason for the broken heart. On addition, there are two more colors that are coded on this interface. Orange is used in the graphs to display the likelihood where as green is for the unlikelihood. This corresponds to the headings **Evidence For** and **Evidence Against**. The colors used were specifically chosen with reasons; red for the color of blood; blue for air (respiratory system); brown being the color of anesthetic bottles; orange for being bright; green is used to show OK (or GO for instance on traffic lights). The use of a shaded orange graph with a green line is to make a clear distinction between the likelihood and unlikelihood.

Lastly we have a status bar that gives extra information to the anesthetist. As mentioned earlier, the probabilities are estimated using data generated from monitoring devices however, some information that could be used to verify a certain diagnosis can only be observed by the anesthetist (see 2.3). We display such information in the status bar at the bottom of the screen. In Figure 2, we advise the anesthetist to check **ECG ST-segment changes** and **Arrhythmia (Irregular ECG)**, which are arguments for Myocardial ischaemia although its probability has been computed based on the values of Forward failure and Backward failure. This interface is a result of consultations with the usability class in the department of Artificial Intelligence, specialists from the University Hospital,
and computer scientists from the department of Mathematics and Computing Science, University of Groningen. With all such aspects put into consideration, the designed system should be very usable and with ease.

3. Discussion And Conclusion

This paper discusses the usability aspects of Diagnesia, a DSS designed to enhance the decision making process of the anesthetists by improving their situation awareness. We discussed a number of aspects that include using probability theory [Miller et al., 1982; Weinstein and Fineberg, 1980] to estimate the likelihood and unlikelihood of disorders in the operating theatre. We present such information to the anesthetist using a graph with a logarithmic scale in order to superimpose the current state of the patient over the historical data. On addition, we present the patients state using icons in order to acquire information about cases that are not familiar to the anesthetist. We also attempt to take into consideration disorders that may be brought about by arguments that we can not measure (perhaps can be observed) as well as those whose values may be unavailable for whatsoever reason.

We have also discusses some challenges still faced with this body of work. Disorders whose arguments can only be observed by the anesthetist are still a challenge. We also need to find a better way of resolving the misinformation brought about by missing or unavailable measurements. Despite the fact that adoption of cognitive models into artificial intelligence systems requires a substantial amount of time [Pauker and Kassirer, 1980], there is more to be done in this body of work with adequate testing in mind.

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